Enhancing agricultural object recognition in UAV data with integrated sensing path planning approaches

Mar Ariza-Sentís

Propositions

1. Efficient Data Collection demands path-planning techniques to streamline agricultural operations. (this thesis)
2. The evidence obtained in experimental farmlands cannot be broadly applied to commercial croplands. (this thesis)
3. Scientific research reaches its maximum profitability when it meets the needs of stakeholders.
4. Publishing datasets and scripts used in manuscripts as open-source enhances research reproducibility.
5. Contemplating opposite viewpoints is crucial to refining argumentation skills.
6. It is essential to integrate multiple perspectives to achieve effective solutions.

Propositions belonging to the thesis, entitled

Enhancing agricultural object recognition in UAV data with integrated sensing path planning approaches

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Enhancing agricultural object recognition in UAV data with integrated sensing path planning approaches

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Thesis

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Contents

Chapters

Gràcies mare, pare i tata
per la vostra paciència, dedicació
i per l'estima que em doneu cada dia.
Us tinc sempre en el cor i en tot el que faig.
Us estimo amb tot el meu ésser.

Chapter 1

Introduction

1.1 Precision farming

Precision farming (PF), also known as precision agriculture, aims to optimise **field-level** management by leveraging data and technology (Blackmore, 1994). It involves **tracking and addressing** within-field variability in crops and soil, thereby ensuring optimal health and productivity. PF integrates tools such as GNSS (Pérez Ruiz and Upadhyaya, 2012), **Remote Sensing** (Seelan et al., 2003), and information technology to boost crop yields, lower input costs, and minimise the environmental impact (Auernhammer, 2001). Implementing PF techniques significantly contributes to farm profitability by optimising **resource efficiency**, ensuring high-quality production, and enabling precise input application, leading to waste reduction and lower operational costs (Griffin et al., 2018).

Precision viticulture, a specialised branch of precision farming, focuses on optimising the cultivation of grapevines (Taylor, 2004). This practice is especially crucial to the wine industry, where the quality and yield of grape production are critical. Precision viticulture utilises detailed information about the vineyard's **soil, environment**, microclimate, and vine health to manage the field on a site-specific basis (Tisseyre et al., 2007). By precisely applying water, fertilisers, pesticides, and monitoring crop health, farmers can enhance **grape quality** and yield while boosting the **sustainability** of the vineyard (Matese and Di Gennaro, 2015).

1.2 Sustainability and Rural Communities

The current Climate Change context in which we are living poses significant challenges to agriculture, making sustainability an essential aspect of modern farming (Bongiovanni and Lowenberg-Deboer, 2004). By employing practices that **optimise water** and nutrient use, farmers can mitigate the effects of **climate variability**, maintain soil health, and reduce greenhouse gas emissions (Roy and George K, 2020). PF methods not only enhance the **resilience** of agricultural systems to Climate Change but also promote long-term sustainability by ensuring that agricultural practices remain environmentally friendly and **economically feasible** (Mylonas et al., 2020).

As a matter of fact, PF holds significant potential for revitalising rural communities, enhancing the efficiency and profitability of agriculture making rural environments more appealing to young generations, promoting their economic growth (White, 2012). The increased viability of rural areas through PF techniques helps to prevent **rural depopulation**, thereby maintaining resilient communities and preserving their **cultural heritage** and traditions (Agnoletti and Santoro, 2022; Sardaro et al., 2021), which are currently at risk due to urban migration. Furthermore, improved efficiency and productivity reinforce **food security** by ensuring a consistent food supply and mitigating the risk of shortages in rural regions (Sibhatu and Qaim, 2017). Consequently, the implementation of PF aligns with the objectives of the **Global Goals** and the **2030 Agenda** for Sustainable Development (United Nations, 2015a).

1.3 Platforms for precision farming

Since the early 1900s, **tractors** have transformed agricultural practices, supplanting animal labour for various farming tasks and significantly increasing agricultural efficiency (Aguilera et al., 2019; Göhlich, 1984). These machines brought a **revolution** in farming practices, enabling more extensive and intensive cultivation of crops. The 1920s and 1930s witnessed the widespread adoption of diesel engines (Baldwin, 2011), which became essential for ploughing, planting, and harvesting, supporting larger-scale operations and contributing to the Green Revolution (Ahmed, 1976). Contemporary tractors are now equipped with **cutting-edge technologies** such as GPS for PF, automated steering, and real-time data collection systems. These technologies enable planting and spraying at variable rates (Pedersen and Lind, 2017; Šarauskis et al., 2022), maximising resource efficiency, which can also be applied to viticulture for efficient management (Matese and Di Gennaro, 2015). The integration of these technologies into traditional farming equipment enhances their capability, making them essential tools in the PF toolkit.

In addition to tractors, other platforms have been developed to improve the application of PF techniques. These platforms encompass Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs), each designed for specific tasks and adaptable to various field sizes.

UAVs, commonly referred to as **drones**, have revolutionised agriculture by offering an aerial perspective that enhances field **monitoring and mapping** (Abdullahi et al., 2015; Singh et al., 2022). They can quickly cover **large areas**, providing high-resolution images that help in assessing crop health, soil conditions, and pest infestations (Maslekar et al., 2020). Besides monitoring, UAVs can execute various field management tasks like spraying (Raj et al., 2020), offering new opportunities for precise and efficient resource applications. Furthermore, UAVs can enter the field at advanced stages of crop development without causing any damage (Velusamy et al., 2022), allowing for **continual intervention** throughout the growing season. In viticulture, UAVs are particularly beneficial for disease assessment (Albetis et al., 2017) and yield prediction (Torres-Sánchez et al., 2021). The aerial perspective offered by drones allows for comprehensive **surveillance** of the vineyard, enabling **early identification** of issues that could impact grape quality and yield. However, since UAVs have only recently been integrated into agriculture, further research is needed to evaluate and improve their applications in PF.

UGVs, or **ground robots**, are primarily employed for tasks requiring **close interaction** with crops, such as soil sampling (Olmedo et al., 2020), weeding (Espinoza et al., 2020), and fruit picking or harvesting (Maja et al., 2021). UGVs are equipped with sensors and tools that enable them to perform repetitive tasks with high accuracy, underscoring their aid to assist in PF tasks. Furthermore, UGVs have the advantage over UAVs in their ability to carry **heavy payloads**, such as larger quantities of phytosanitary products (S. Wang et al., 2022). In viticulture, these robots can manoeuvre between rows, maintaining close contact with the crop, making them ideal for crops trained in vertical trellis systems. However, a disadvantage of UGVs is their potential **difficulty** in navigating **muddy terrains** or those with stones, obstacles, or steep slopes (Santos et al., 2022, 2021). Similar to UAVs, more research is necessary to fully evaluate and improve their potential.

1.4 Revolutionising precision farming with artificial intelligence

Artificial intelligence (AI) is revolutionising agriculture by simplifying data analysis and decision-making (Duan et al., 2019; Zhang and Zhang, 2022). AI involves the simulation of human intelligence in machines, enabling them to perform tasks such as reasoning, learning, and problem-solving. **Machine Learning** (ML), a subset of AI, uses algorithms and statistical models to allow machines to improve their performance through experience (Alpaydin, 2021). **Deep Learning** (DL), an advanced subset of ML, employs neural networks with multiple layers to analyse complex data patterns (LeCun et al., 2015).

In agriculture, these technologies are used to develop intelligent systems capable of analysing large datasets and making informed decisions (Durai and Shamili, 2022). **Object detection and tracking** are key applications of AI in agriculture (Osman et al., 2021). Object detection identifies specific objects within an image, such as plants, fruits, or machinery, while tracking monitors their position over time. These capabilities are essential for **automating** agricultural tasks like fruit picking (Zhao et al., 2022; Chan Zheng et al., 2021), disease detection (Dwivedi et al., 2021; Y. Zhang et al., 2020), and crop growth monitoring (Pratama et al., 2020a; Santos et al., 2020).

This **technological integration** of techniques with UAVs, UGVs, and tractors offers a comprehensive solution for automating farm processes and optimising resource allocation (Liu et al., 2021). By combining data from these platforms, detailed insights and precise recommendations are provided. Automating routine tasks allows farmers to focus on strategic aspects of farm management, with AI-driven systems ensuring decisions are based on accurate, up-to-date information, thereby **reducing labour costs** and improving overall farm management **efficiency** (Botta et al., 2022; Saiz-Rubio and Rovira-Más, 2020).

The adoption of advanced technologies in PF not only improves agricultural practices but also generates new **job opportunities** in rural areas. These positions are often less physically demanding and provide **better working conditions** and higher wages, attracting a more **diverse workforce**. For instance, more engineers, computer scientists and data analysts are needed. As more people find work in rural areas, the demand for services grows, thereby stimulating the **tertiary sector**. This includes the need for additional schools, hospitals, supermarkets, and other **essential services**, which subsequently ensures quality education, improved healthcare, and reduced inequalities compared to urban areas. These advancements foster inclusive and sustainable growth for **rural communities**.

1.5 Problem definition

Technological integration in the field of agriculture presents numerous advantages. Nevertheless, current applications mostly focus on the analysis phase, for instance, the application of object detection and tracking algorithms (Gao et al., 2022; Santos et al., 2020; Wenli Zhang et al., 2022a), rather than on its prior step: **data acquisition**. This shift in focus is crucial because the agricultural environment is constantly varying since it is characterised by **living beings** that require **continuous monitoring** and adaptation of the biophysical environment (Ara et al., 2021; Zhai et al., 2020).

Enhanced data acquisition in agriculture requires meticulous planning and regular surveys to account for its **changing conditions**. In that regard, this thesis proposes a **two-phase framework** (Figure 1.1) to optimise data collection in vineyards, addressing several challenges. Each phase requires distinct mission planning algorithms to accommodate their different operational needs, ensuring that data collection is both comprehensive and targeted.

The first phase involves a **general mapping** of the vineyard by surveying the field from a certain height, for instance, at 20 or 30 meters height, depending on the size of the field. This first flight is useful to obtain an **up-to-date overview** of the vineyard and to identify its current status, such as the number of missing vine plants or assess the presence of a disease. However, this general mission is insufficient to extract specific information about grape bunches and hence, a close-to-plant flight is required.

The second phase focuses on **closer-view mapping** for specific purposes. This phase aims to gather **detailed information** on grape bunches, including phenotypic traits and health status, which are crucial for effective yield prediction and disease detection. However, the task is complicated by **occlusion**, where grape bunches are often hidden behind leaves and branches. Leaf removal is not a feasible solution due to its high cost and lack of benefit to farmers. To address this issue, this thesis develops a **multiple-angle path planning** approach so that grape bunches are observed from several perspectives. This method enhances data collection by managing the occlusion problem, enabling more accurate monitoring of the plants from a closer distance during the second phase.

Figure 1.1. Two-phase framework proposed to map the field with two levels of detail: from above to get an overview of the vineyard environment, and from below to gather detailed grape bunch information at plant level.

1.6 Objective and research questions

The main objective of this thesis is to establish a framework aimed at enhancing data collection in order to boost object detection and tracking for PF to improve agricultural operations such as disease assessment for precision spraying and phenotyping for yield forecasting, considering the field environment and avoiding fruit occlusion.

To evaluate the current status and challenges of technological integration in PF, a comprehensive review of the current technologies and their limitations was performed (RQ1). A key challenge observed was the emphasis on data acquisition, resulting in the development and application of a two-phase framework to monitor the vineyard environment and to assess the presence of diseases through a disease factor assessment analysis (RQ2). To mitigate fruit occlusion, the developed framework included a multi-angle perspective (RQ3). For validation, the proposed approach was tested against a single-angle method (traditional data acquisition) by comparing grape bunch detection and tracking metrics, fruit counting, and phenotypic trait correlation (RQ4).

The research questions of the thesis are the following:

RQ1: What are the current status and challenges of integrating object detection and tracking in precision farming?

RQ2: How can a two-phase framework be used to monitor and manage vertical-trellis crops efficiently?

RQ3: How can fruit occlusion be mitigated, and what is the effectiveness of including multi-angle perspectives?

RQ4: How does the proposed framework compare to a single-angle method?

1.7 Thesis outline

To reach the objectives of the thesis, several studies were conducted. The structure of the remaining chapters of this thesis is as follows:

Chapter 2 examines the current advancements in object detection and tracking within the context of PF. It scrutinises key areas of focus in contemporary research, primarily the enhancement of algorithms. The chapter also emphasises the importance of considering the field environment for optimal data acquisition. Lastly, it addresses the scarcity of open-source datasets, highlighting the issue of non-reproducibility.

Chapter 3 investigates the application of the two-phase framework in a specific use case: spraying. The second phase (mapping from below), includes three different platforms (UAVs, UGVs, and tractors) as it examines each platform's efficiency, cost-effectiveness, and sustainability, providing a comparative analysis to determine the most suitable platform for this task at different risk levels. The chapter includes an open-source dataset used to assess the presence of the disease.

Chapter 4 applies a generic approach to object detection and tracking to the specific task of detecting grape bunches and berries, with a particular focus on phenotyping. The chapter details the methodology and the results of applying this approach in a practical scenario, providing an open-source dataset to validate the findings.

Building on the challenges identified in the previous chapter, *Chapter 5* introduces a theoretical approach to UAV path planning. It considers multiple viewing points to avoid occlusion as a strategy to improve the accuracy and efficiency of grape bunch detection.

Chapter 6 takes the theoretical path planning model developed in *Chapter 5* into a real-world scenario. The validation process is described in detail, demonstrating how the proposed path planning method enhances grape bunch detection metrics. Further, it provides an open-source dataset to enhance reproducibility.

The final chapter (*Chapter 7*) provides a comprehensive review and reflection on the findings from *Chapters 2* through *6*. It synthesises the key insights gained from the research and discusses their implications. The chapter also outlines potential directions for future research, addressing challenges and proposing new areas of investigation to advance the field of precision farming and precision viticulture.

Chapter 2

Object detection and tracking in precision farming: a systematic review

This chapter is based on:

Ariza-Sentís, M., Vélez, S., Martínez-Peña, R., Baja, H., Valente, J., 2024. Object detection and tracking in Precision farming: a systematic review. Computers and electronics in Agriculture. 219, 108757. https://doi.org/10.1016/j.compag.2024.108757

Abstract

Object detection and tracking have gained importance in recent years because of the great advances in image and video analysis techniques and the accurate results these technologies are producing. Moreover, they have successfully been applied to multiple fields, including the agricultural domain since they offer real-time monitoring of the status of the crops and animals while counting how many are present within a field/barn. This review aims to review the current literature on object detection and tracking within the field of PF. For that, over 300 research articles were explored, from which 150 articles from the last five years were systematically reviewed and analysed regarding the algorithms they implemented, the domain they belong to, the difficulties they faced, and which limitations should be tackled in the future. Lastly, it examines potential issues that this approach might have, for instance, the lack of open-source datasets with labelled data. The findings of this study indicate that object detection and tracking are critical techniques to enhance PF and pave the way for robotisation for the agricultural sector since they provide accurate results and insights on crop and animal management and optimise resource allocation. Future work should focus on the optimal acquisition of the datasets prior to object detection and tracking, along with the consideration of the biophysical environment of the farming scenarios.

2.1 Introduction

Due to the constant increase in population (United Nations Department of Economic and Social Affairs, Population Division, 2022), the reduction in the amount of arable land (Azadi et al., 2011), and the unpredictable and increasingly severe climate patterns due to climate change, the current agricultural and food production systems are facing several challenges (Misra, 2014; Pereira, 2017). Precision farming (Blackmore, 1994) originated from the need to farm with limited resources applying only the inputs that are required by the crop to enhance the productivity of the field while conducting the most sustainable farming practices and taking into consideration the environment (Auernhammer, 2001). Addressing these challenges through PF offers substantial economic and sustainability benefits. For instance, targeting chemical interventions allows enhanced economic viability for the farmer, but also contributes to sustainability by minimising waste, reducing the environmental footprint, and ensuring long-term food security for a growing population (Bongiovanni and Lowenberg-Deboer, 2004; Martos et al., 2021).

Recent technological advancements offer innovative tools that harness their capabilities for diverse agricultural applications. These technologies include satellite (Vélez et al., 2022) and UAV-based remote sensing (Sishodia et al., 2020; Tsouros et al., 2019), data analytics, and Computer Vision tasks, which have empowered farmers with new tools to tailor farming practices to specific conditions and needs, improving the traditional image processing techniques and reducing the manual tasks required. These include the precise identification of pests and diseases, enabling accurate and precise chemical applications (Ariza-Sentís et al., 2023c; Qiang and Shi, 2022; Vélez et al., 2023a), comprehensive vegetation assessments (Campos et al., 2019; Chang et al., 2020; Matese et al., 2017; Vélez et al., 2021, 2020), insights into crop physiology (Lacerda et al., 2022), detailed analyses of plant structure (Escolà et al., 2023; S. Xiao et al., 2023), plant water stress assessment (Bellvert et al., 2015; Gutiérrez et al., 2018) and the evaluation of quality and biophysical parameters (De Grave et al., 2020; Frampton et al., 2013; Gatti et al., 2022; Martínez-Peña et al., 2023b, 2023a; Matese et al., 2022). Furthermore, the adoption of automation and robotics for farming purposes has streamlined labour-intensive tasks, such as visual inspections of the fields and farms, making farming more efficient and sustainable (Marinoudi et al., 2019).

In particular, DL (LeCun et al., 2015; LeCun and Bengio, 1995) has shown important advances in agriculture in performing various important tasks such as plant phenotyping, yield estimation, crop classification, or disease detection (Ariza-Sentís et al., 2023b; Bouguettaya et al., 2022; Kamilaris and Prenafeta-Boldú, 2018; Zhou et al., 2023). In addition, when DL-based object detection is integrated with tracking, it gives rise to a distinct field known as " object detection and tracking", an area that has seen rapid growth in recent years, driven by advancements in GPU computing power (Davies, 2004), mainly due to the decrease in their costs, and the boost in image analysis techniques. Hence, the number of research studies performed on those domains has increased significantly, drawing significant attention to DL projects (Vargas et al., 2017). Object detection along with object tracking offers a robust approach compared to object detection alone since it presents several advantages across applications. While object detection identifies objects in static frames, the integration of tracking provides temporal continuity, which enables object counting and trajectory analysis (Ahmed et al., 2019). Further, it generates richer datasets due to object-tracking across frames, which enhances accuracy and boosts informed decision-making. Moreover, the combination of object detection and tracking preserves the identity of the object, aiding in scenarios involving occlusion (Babaee et al., 2018; Lee et al., 2014).

The agricultural and livestock domain has also benefited from this trend. Object detection and tracking techniques have shown great potential to enable behaviour analysis and object interactions, which is crucial for applications like autonomous vehicles and enhancing animal welfare (Khairunissa et al., 2021); allowing plant ID recovery even if a plant temporarily leaves the view of the camera, ensuring individual plant recognition and avoiding repeated spraying by the robot (Hu et al., 2022); or to develop key tasks such as detecting plants and their fruits (de Jong et al., 2022; Wenli Zhang et al., 2022b), which eases the inspection time which is currently carried out by field operators. Moreover, object detection and tracking permit the automation of crop harvesting to improve field productivity and optimise operational costs (Junos et al., 2021), paving the way for the robotisation of the agricultural sector. Furthermore, object detection and tracking allow for precise monitoring and management of livestock animals' movement (Huang et al., 2023; Myat Noe et al., 2023). It facilitates real-time analysis of behaviours and health metrics, which optimises care and resource allocation for each individual animal.

The challenges and applications of DL in agriculture have been comprehensively addressed in prior surveys (Alibabaei et al., 2022; Bouguettaya et al., 2022; Kamilaris and Prenafeta-Boldú, 2018; D. Wang et al., 2022). However, there is a notable absence of literature reviews specifically focusing on the integration of object detection and tracking in enhancing PF techniques. Consequently, the motivation for writing this review article was to address the need for a comprehensive analysis of the utilisation of Computer Vision and DL techniques applied to object detection and object tracking within the field of PF, considering the increasing interest in this sector and the potential transformative effects on food security and fostering sustainable agricultural practices. To the best of our knowledge, this is the first review conducted in the field of object detection and tracking applied to PF. This review aims to solve two research questions:

RQ1: What are the current advancements, challenges, and potential future research lines in the implementation of Computer Vision and Deep Learning methods within precision farming?

RQ2: How can the integration of Computer Vision and Deep Learning techniques in precision farming be optimised to maximise their impact?

The paper is structured as follows: Section 2 explains the methodology followed in this study to select and revise the research articles that exist inside the domain of study. After, Section 3 introduces the concept of object detection and tracking, their applications, and how they have evolved until the present. Section 4 includes the most-known algorithms for object detection and tracking used in the field of PF, along with several use cases that have already shown a lot of potential within the agricultural field and the conceivable problems that were found in the literature. Finally, Section 5 and Section 6 include the Discussion and Conclusions, respectively.

2.2 Methodology

This review systematically analyses the current literature related to object detection and tracking within the field of PF, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

Regarding the protocol and registration, the systematic review was conducted retrospectively, involving three main steps to carry out the bibliographic analysis: (1) identification of the available work, (2) filtering out work not related to the agricultural and livestock domain, and (3) meticulous and precise review for each of the papers collected in the previous step. Regarding the filtering stage, it aimed to refine the dataset and enhance the relevance of the selected papers. This step was necessary because, despite papers being searched with keywords belonging to the agricultural and livestock domain, some articles also appeared in the search results and, to solve that, the filtering step was required. For information sources, the search was conducted in three scientific databases (accessed between April 4th and April 6th, 2023): ScienceDirect ("ScienceDirect," 2023), Springer ("Springer," 2023), and Google Scholar ("Google Scholar," 2023), chosen for their extensive coverage of the scientific literature in technology and agriculture. Eligibility criteria for studies covered by the review included journal articles and conference papers published in English within the last five years (2018-2023) to ensure the inclusion of recent and up-to-date research findings.

The search strategy combined keywords to adequately cover the scope of the study, and the following four search keywords were introduced in each of the three mentioned datasets:

- "Object detection and tracking" AND "agriculture" OR "farming"
- "dataset" AND "Object detection and tracking" AND "agriculture" OR "farming"
- "Object detection" AND "agriculture" OR "farming"
- "tracking" AND "agriculture" OR "farming"

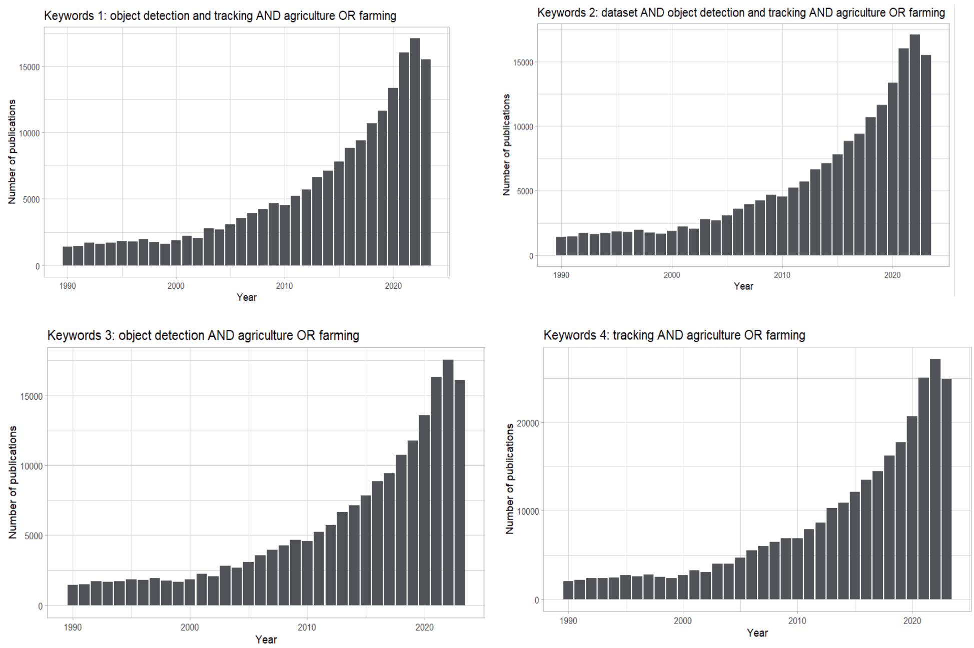


Figure 2.1. Bar chart representations of the number of research papers found in ScienceDirect when the four research keywords mentioned were introduced.

An overview of all the research articles found utilising the four mentioned search keywords in ScienceDirect is shown in Figure 2.1. In the study selection process, a total of 150 papers were retrieved from each database, resulting in a combined initial dataset of 450 papers, from which 150 were filtered because they belonged to the agricultural and livestock domains. In addition, some interesting additional documents were added to this review, extracted from the references of the retrieved articles, for instance, databases and other reviews. The data collection process was systematically executed, with key information from each paper being documented, such as authors, publication year, and main results related to object detection and tracking techniques within PF. Extracted data included detailed study characteristics such as objectives, methodology, outcomes, and findings pertinent to the study scope.

To answer these research questions, each selected paper was reviewed and examined, the findings were documented, and key information about the research questions was extracted from each paper. The primary measure for synthesis was the contribution of each study to the understanding of object detection and tracking techniques, considering the effectiveness and applicability of the research. Finally, the synthesis of results employed a qualitative narrative approach due to the diversity of methodologies and outcomes present in the literature, providing a comprehensive understanding of the current state of research in the domain.

All these steps aimed to provide a comprehensive understanding of the current state of research related to object detection and tracking techniques in the agricultural and livestock domain.

2.3 Object detection and tracking

Object detection and tracking are a branch of DL and Computer Vision that is used to identify and follow instances of visual objects belonging to different classes within their environments (Porikli and Yilmaz, 2012; Yilmaz et al., 2006). It has evolved with time regarding the algorithms and architecture implemented (Figure 2.2), having a further and deeper development during the 2010s for object detection and during the 2020s for object tracking. Object detection and tracking have already been applied to several domains. A relevant area of application is person identification for video surveillance systems (Fradi et al., 2018; Tang et al., 2014), to ensure social-distancing rules during Covid-19 pandemic (Punn et al., 2021), to estimate the human pose (Wang et al., 2020), and for people counting in crowded scenarios (Salim et al., 2019; Sidla et al., 2006), obtaining promising results that explain the increased focus they received in recent years. Another domain that has greatly benefited from the advances in object detection and tracking is vehicle detection for smart transportation and surveillance systems (Amrouche et al., 2022; Hassaballah et al., 2021; Wang and Zhang, 2022), for enhanced autonomous driving (Sadik et al., 2022; Wael, 2020), and for number-plate identification, which can be used to fine any traffic-rule violations (Babu and Raghunadh, 2016), among other utilisations. However, to optimise these AI applications and achieve high-performance metrics, it is essential to consider multiple processing steps and the modifications made since their inception.

2.3.1 Evolution of object detection

R-CNN (Girshick et al., 2014) started in 2014 to improve Convolutional Neural Networks (CNN). It presented a novel two-stage detection architecture, which extracted regions in an image, called proposal regions, which used a selective method to combine images into larger ones. It was then fed into a Support Vector Machine (SVM) (Noble, 2006) to classify whether a specific region contained an object. This approach was faster than its predecessors, but at the time it was still incapable of real-time detection.

Fast(er) R-CNN (Girshick, 2015; Ren et al., 2015) was developed as an improvement to R-CNN. It enhanced the previous algorithm by creating a convolutional feature map that saved the region of the images, avoiding feeding multiple regions into the SVM over and over, which improved the speed of training and detection significantly. A succeeding advancement to Fast(er) R-CNN, proposed by He et al. (2017), was Mask R-CNN, which aimed to increase the accuracy of detected objects by applying instance segmentation on top of bounding boxes. The mask of each object was added just as an overhead to not affect the training and detection time significantly. Mask R-CNN was beneficial in detecting and recognising packed objects such as cars in traffic, people in crowds, and other objects that need per-pixel accuracy to differentiate.

After Fast R-CNN and its modified version Faster R-CNN were made, more efficient methods were developed that only had a one-stage detection step; (1) YOLO: You Only Look Once (Redmon et al., 2016) and (2) Single Shot Multibox Detector (SSD) (Liu et al., 2016). Unlike Fast(er)R-CNN and its predecessors, YOLO and SSD were detectors with a single stage. They applied a single neural network to the entire image, rather than extracting and verifying proposal regions. The neural network divided the image into many regions before simultaneously predicting and estimating bounding boxes and classes without an intermediate region proposal stage. Compared to its two-stage equivalents, the architecture of YOLO and SSD detected objects far more quickly than its two-stage counterparts, which expands their applicability to real-time detections. Nevertheless, these models might struggle with detection accuracy, especially in the case of small objects. Hence, it is relevant to choose the algorithm to be used considering the trade-off between detection accuracy and speed.

YOLO has also received many incremental improvements such as YOLOv2 and YOLOv3 (Redmon and Farhadi, 2018, 2017). With each iteration, the speed and accuracy of YOLO improved significantly. YOLOv3 achieved a detection speed almost 100x (100 times) faster than Fast(er) R-CNN. However, YOLO was not accurate in identifying small objects in an image. There have been more iterations of YOLO (YOLOv2 to YOLOv8), which have tried to alleviate this problem while simultaneously improving the accuracy and speed. Lastly, EfficientNet (Koonce, 2021) is a CNN architecture developed by Google Research that uses a compound coefficient to uniformly scale all the dimensions (depth, width, resolution).

2.3.2 Evolution of object tracking

Object tracking in Computer Vision typically involves processing a series of images or an entire video. Earlier algorithms often employed a technique that separated each frame's moving object from the background (Wang et al., 2000), then developed a track for the detected object. However, due to the limitations at that time, there were many problems such as tracks being lost, low FPS, limited track numbers, and inaccurate detections. Nowadays, with the improvement of detection algorithms, object tracking is done in two steps: Object detection using a detection algorithm, and then tracking the identified object. This framework is called *tracking by detection* (Leibe et al., 2007).

The *tracking by detection* framework is the most widely researched method of tracking. The tracking step is done by utilising different methods such as optical flow (Horn and Schunck, 1981) and Kalman filter (Welch and Bishop, 2006). Other more modern methods include 3D convolutional layers (Carreira and Zisserman, 2017).

Multi-Object Tracking (Leal-Taixé et al., 2015) has become a valuable Computer Vision task. Nevertheless, since the tracking is based on simple bounding boxes, its accuracy is reduced when objects are occluded. Furthermore, Multiple Object Tracking (MOT) can utilise historical information within videos, which can be useful during the evaluation and identification of agricultural objects to achieve multi-surface detection of these products (Y. Chen et al., 2021).

Multi-Object Tracking and Segmentation (MOTS) included instance segmentation to solve the issue mentioned above. It was developed by Voigtlaender et al. (2019), together with TrackR-CNN, the first end-to-end trainable framework for object tracking. It used the Mask R-CNN detection algorithm in conjunction with two 3D convolutional layers to give the algorithm the ability to associate detections over time, while also dealing with the temporal dynamics of the image sequence. Subsequently, TrackR-CNN decided which detections were the same between images with the help of the Hungarian algorithm. With the information it acquires, it subsequently links the detections over time. While it is a reliable tracking algorithm, there are several other more state-of-the-art algorithms to improve the tracking performance of TrackR-CNN.

Following the introduction of TrackR-CNN, several MOTS algorithms were developed, such as PointTrack (Xu et al., 2020), ViP-DeepLab (Qiao et al., 2020), ReMOTS (Yang et al., 2019), ByteTrack (Y. Zhang et al., 2022), and StrongSORT (Du et al., 2023), among many others. A common characteristic of the algorithms presented above is that all of them have been tested using a dataset annotated with MOTS standards that includes the classes of pedestrians and cars, called KITTI MOTS (Geiger et al., 2013). However, there are several different characteristics of each algorithm regarding the method of functioning. PointTrack reaches accurate metrics by converting images into 2D point cloud representations, which permits a tracking-by-points system (Neven et al., 2019). Instead, ViP-DeepLab implements 3D point clouds to estimate the class, spatial location, and temporal location of each point cloud (Nguyen and Le, 2013). ReMOTS employs a straightforward self-supervised method to enhance tracklets (a cluster of frames generated by the system) derived from predicted masks. ByteTrack operates on binary features extracted from object templates, which significantly reduces computational burden and memory usage. Finally, StrongSORT is the fusion of appearance and motion information, which allows the creation of robust and discriminative embeddings that are capable of encoding spatial and temporal information about tracked objects.

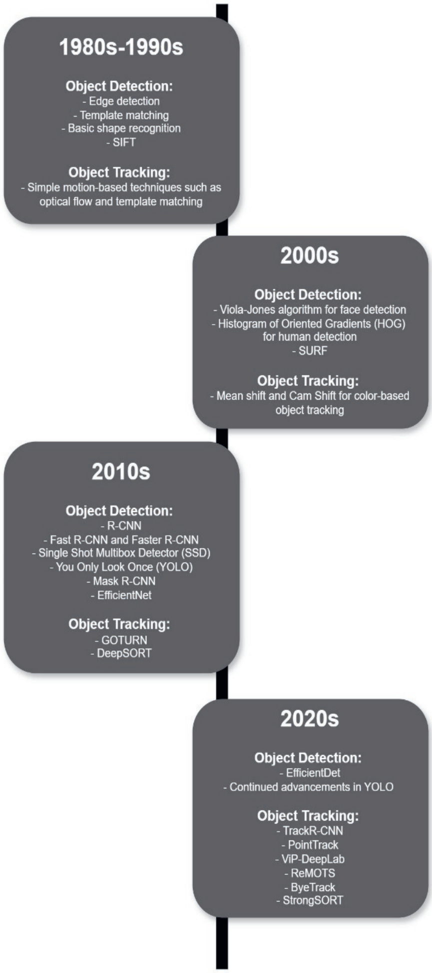


Figure 2.2. Timeline of the evolutionary milestones in object detection and tracking, showcasing the progression of key algorithms and architectures from foundational approaches in 1980 to recent advancements in the 2020s, demonstrating the continuous innovation in Computer Vision over time.

2.4 Object detection and tracking applications in precision farming

There have been many advances in object detection and tracking in several fields. However, they do not always easily apply to agriculture and farming because of the complexities and particularities of the domain, such as homogeneity and occlusion of objects, which complicates the tracking task. Hence, they require tailor-made solutions that adapt to the specific challenges (Pezzementi et al., 2018).

All the relevant works regarding object detection and tracking within precision agriculture, which were examined and selected according to the process described in the Methodology, are discussed in detail in this section. It starts by introducing the most commonly used algorithms and afterwards, it separates the papers concerning the research area that they belong to, and it ends by providing the issues that this topic is currently facing.

2.4.1 Object detection and tracking algorithms

There is a great variety of algorithms used for object detection and object tracking. For object detection, CNNs, a type of artificial neural network for recognising patterns in images, are the most popular algorithms currently in use (G. Xu et al., 2022). Further, many CNN algorithms have been developed and published open-source in recent years, which has boosted the progress of CNNs used for object detection in PF (Fuentes et al., 2017; Magalhães et al., 2023; Wosner et al., 2021). A very well-known CNN-based algorithm is YOLO, and all its developed versions, including tracking in the latest version, called YOLOv8. There is a great variety of research papers regarding object detection in PF that have utilised YOLO algorithms for the identification of the target topic (Mota-Delfin et al., 2022; Myat Noe et al., 2023; X. Xu et al., 2022).

Regarding object tracking, Deep Simple Online and Realtime Tracking (Deep SORT) (Wojke et al., 2017) has shown potential while obtaining high-tracking precision and accuracy metrics (Osman et al., 2021) since the algorithm tracks objects based on their appearance.

Table 2.1 provides a comprehensive summary of the five emerging methods that are widely used in the domain of object detection and tracking in PF.

Table 2.1. Most relevant algorithms used in object detection and tracking in precision farming.

Name of the algorithm	How it works
Scale-Invariant Feature Transform (SIFT)	- **Function**: Identifies and matches features in an image. - **Advantages**: Robust to changes in scale, rotation, and illumination.

(Solis-Sánchez et al., 2011; Yao et al., 2015)	- **Explanation**: SIFT detects and describes local features in images, making it ideal for object recognition or matching images across different perspectives.
Simple Online Realtime Tracking (SORT) **(He et al., 2022; Yang et al., 2022)**	- **Function**: Identifies objects in the frame that are to be tracked. - **Advantages**: Lightweight and fast, suitable for real-time tracking. - **Explanation**: SORT computes a cost matrix based on the Intersection over Union (IoU) distance between detection and prediction locations, refining object tracking.
Speeded Up Robust Feature (SURF) **(Rahmat et al., 2018; Rani et al., 2022)**	- **Function**: Detects and describes image features. - **Advantages**: Faster and more efficient than SIFT, suitable for real-time applications. - **Explanation**: SURF uses integral images and a series of filters to quickly identify interest points in an image.
Convolutional Neural Network **(Čirjak et al., 2023; Ganesh et al., 2019; M. Li et al., 2020)**	- **Function**: Trains on large datasets to identify objects or features in images. - **Advantages**: Highly accurate for image classification and object detection tasks. - **Explanation**: CNNs use layers of convolutions to automatically and adaptively learn spatial hierarchies of features from images. - Model Examples: i. **Fast R-CNN**: Uses selective search to generate Regions of Interest, speeding up the detection process. ii. **Faster R-CNN**: Introduces a Region Proposal Network (RPN) to generate region proposals directly. iii. **Mask R-CNN**: Adds a branch for predicting segmentation masks on each Region of Interest. iv. **YOLO**: Detects objects in a single forward pass of the network.

	v. **SSD** (Single Shot MultiBox Detector): Detects objects in various aspect ratios using a single forward pass, making it faster than many other methods. vi. **EfficientNet**: Optimised for performance and efficiency, often used as a backbone for more complex tasks. vii. **EfficientDet**: Builds on the EfficientNet architecture, offering state-of-the-art accuracy with fewer parameters and smaller model sizes.
Mean Shift (Friedman et al., 2013; Sun et al., 2019)	- **Function**: Estimates the mode of a distribution to find the most likely position of an object. - **Advantages**: Non-parametric and doesn't assume any prior shape on the data distribution, making it versatile. - **Explanation**: Mean Shift iteratively shifts a window towards regions of higher pixel density, tracking objects based on their previous location and movement.

There are more algorithms used in PF. However, the ones mentioned in Table 2.1 are the ones most commonly used and the ones that provide the highest metrics. Nevertheless, the selection of the algorithm depends on many variables, such as the type of application, the number of accessible images and/or videos for training the algorithm, the type and size of the object to be detected and tracked, and the computational resources available (El-gayar et al., 2013).

2.4.2 Successful use cases

Since the development of object detection and tracking, there have been many research papers focused on enhancing the current methodology used in agricultural and farming systems, such as greenhouse detection (M. Li et al., 2020) to monitor agricultural activities and land use management, and anomaly detection (Christiansen et al., 2016) in order to identify obstacles for tractors and animals, such as humans.

Some of them combine both agriculture and livestock fields of study. For instance, Sadgrove et al. (2017) performed real-time feature extraction and object classification in agricultural landscapes, allowing for weed detection, together with cattle and quad bike identification (Sadgrove et al., 2018), which enables future research on intelligent cultural machine auto-guidance.

Another related paper was presented by Qiu et al. (2020), where they used an improved version of YOLOv3 and Deep SORT with a mean intersection over union (mIoU) score of 0.779 to detect and track moving obstacles, such as humans and water buffalos. They aimed to develop an obstacle avoidance system for smart agricultural equipment operating in rice fields. Further, Yun et al. (2021) proposed a stereovision method for auto-guidance of a cultivator which was based on detecting and tracking the inter-rows between ridges and furrows. They were able to classify ridges and furrows with an accuracy above 90% under outdoor conditions, with an RMSE ranging from 2.5 to 6.2 cm, depending on the terrain, whether flat or hillside.

2.4.2.1 Horticulture and floriculture

The majority of the research papers found regarding object detection and tracking in horticulture focus on tomatoes in greenhouses as the subject of study. In 2021, a real-time robotic system for tomato fruit growth monitoring in greenhouses was developed (Seo et al., 2021). It reached 88.6% of detection accuracy including fruits that were completely obscured to the camera and 90.2% when those fruits were excluded. It showed potential to use the system to predict harvest times, and yield, and to develop a harvesting robot. In 2022, Ge et al. (2022) included the yield prediction and improved the detection accuracy by comparing Deep SORT and YOLOv5 (Figure 2.3). The former showed better metrics, with a mean average precision (mAP) of 93.1%, 96.4%, and 97.9% for flower, green tomato, and red tomato detection, respectively, representing a 17%, 2%, and 2.3% improvement compared to the results obtained with YOLOv5. In 2023, an improved method for tomato cluster yield estimation in greenhouses was proposed (Rong et al., 2023). It used the improved version YOLOv5-4D trained with data augmentation methods and reached 97.9% detection accuracy and a mAP of 0.748. ByteTrack was adopted to track tomato clusters since it is specifically designed to overcome ID-shift problems. Nonetheless, there was still a counting error of 4.9% due to ID shifting. Future work in the field of object detection and tracking for tomatoes involves classifying tomato maturity to provide more accurate yield estimation.

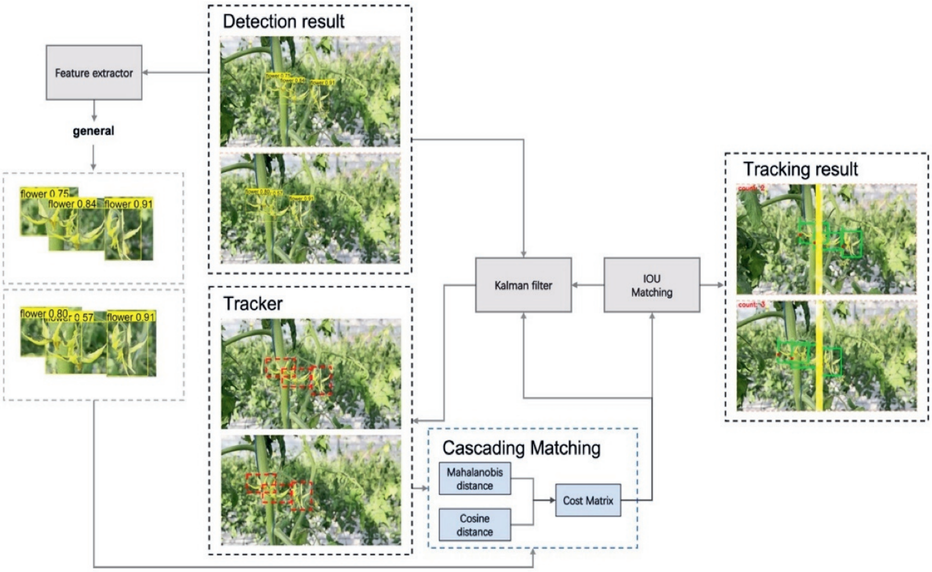


Figure 2.3. Object tracking framework for yield prediction in tomatoes in greenhouses. Source: Ge et al. (2022).

The biggest challenge identified in the strawberry harvesting field is regarding the ripeness of the fruits since they are commonly surrounded by obstacles to be avoided to properly automate the harvesting task. Xiong et al. (2021) combined YOLOv4 and Deep SORT to focus on the target during picking, even if the fruit was partially occluded by the gripper. They reached a 62.4% accuracy rate, which improves by 36.8% the metrics obtained in previous work. Future work involves working with multi-view perception to avoid fruit occlusion to the greatest extent.

Apart from horticulture, there is a great industry devoted to Floriculture, which consists of the production of plants that produce colourful and showy flowers. Houtman et al. (2021) presented an automated flower-counting method that considered multiple viewpoints to avoid flower occlusion. It was tested on Phalaenopsis plants and was capable of tracking the flower movement even when those were not observed. They employed the Multiple Hypothesis Tracking (MHT) approach with a connected and an unconnected flower plant model. The achieved accuracy was 92% for the model connected with the flower plant model, 70% for the unconnected, 58% with a heuristic method, and 44% for a single-image approach. The high accuracy of the connected model was explained indicating that it reduced underestimation caused by flower-occlusion. Future work involves the estimation of the flower size.

2.4.2.2 Grain, fibre, and plantation crops

Among the grain and fibre category, cotton is the most studied, accounting for 50% of the research, followed by corn, likely because cotton and corn have higher revenue than other grain crops, such as barley and wheat (Singh, 2016). Hence, most of the research focuses on those crops. Regarding cotton, Yang et al. (2022) implemented an anchor-free object detection model based on CenterNet and Deep SORT with MOTS to prevent repeated counting (ID switching) of cotton seedlings. In this process, the method used a track confirmation mechanism for the unmatched trackers, which were assigned to unmatched detections. After, they were classified as *tentative* during the three following frames, until it was confirmed, in which case they stayed, otherwise, they were rejected. They obtained an R^2=0.967 and RMSE=0.394, indicating its potential for other applications. Also in 2022, Tan et al. (2022) combined YOLOv4 and optical flow to enhance tracking speed. The F1 score obtained was 0.98, the average precision was 99.12%, an ID switch of 0.1%, and a relative error for counting across videos of 3.13%. The counting speed increased from 2.5 to 10.8 frames per second, offering the possibility of tracking cotton seedlings in real time. However, the model failed to detect seedlings with different shapes, small sizes, and extreme occlusion conditions, a problem that might be solved by training the model with additional data.

With respect to corn, Zhang et al. (2020) proposed a low-cost robot to automate plant trait extraction to reach efficient phenotyping in corn plants. Moreover, the robot was capable of counting corn stands by autonomously driving through the field. Faster R-CNN trained with only 169 images was used to detect corn plants in RGB images, obtaining accurate results and an RMSE of -3.78%. The algorithm was tested on 53 plots and obtained an R^2=0.96 when compared to ground truth data. Future work involves augmenting the training data to avoid underestimating the corn population. It was the first step towards autonomous field robot real-time phenotyping for corn.

Lastly, Zhao et al. (2020) introduced the problem of missing open-source datasets and pre-trained models for bale detection, which are also affected by varying illumination conditions as is also the case of tea buds (Figure 2.4). They trained YOLOv3 with 243 images counting with good illumination conditions and also combined the model with data augmentation. The detection accuracy obtained regarding illumination, shadow, hue change, and snow conditions were enhanced by 15%, 26%, 10%, and 28%, respectively. The detection accuracy was at least 80% for all conditions. Future work involves acquiring more images to train the algorithms and make them robust enough to be implemented under all conditions and potentially other crops. Another important issue while trying to detect and track continuous crops such as grain and fibre crops is occlusions. As already mentioned, multiple-camera systems can provide a solution to this, however, they introduce the concern regarding camera calibration and object matching (Khan and AlSuwaidan, 2022).

(a) (b) (c)

Figure 2.4. Tea bud detection for (a) low, (b) medium, and (c) high brightness images. Adapted from (Yang Li et al., 2023).

2.4.2.3 Woody crops

Woody crops are the category within precision agriculture with the most research papers regarding object detection and tracking since tree and crown detection (Selim et al., 2019) together with fruit detection (Y. Chen et al., 2021) have gained a lot of importance to monitor tree growth, fruit size (C. Zhang et al., 2021) and also to predict the yield to be harvested at the end of the campaign to contribute to the development of intelligent orchards (Lyu et al., 2022). Among woody crops, apple trees, citrus trees, and grapevines are the most studied. Moreover, woody crops such as apple and citrus trees share a lot of common characteristics. For instance, the colour of the fruit is different from the canopy once it is ripe and ready to be picked. Also, the fruit's round shape, size, and geometry, which enables the research performed for one crop can easily be applied to the other crop.

Most of the studies devoted to fruit identification have obtained high metrics above 90% regarding the detection accuracy of the fruits (Ganesh et al., 2019; Kestur et al., 2019; Tu et al., 2020). However, some difficulties arise once tracking is added. Several articles have studied the detection and tracking of apples, oranges, lemons, and avocados, concluding that the biggest challenge found was that there is an occlusion factor during image acquisition and the creation of ground truth data (He et al., 2022; Villacrés et al., 2023; Wang et al., 2016) along with the dependency of the algorithm on the quality of the training set (Vasconez et al., 2020; Xu and Mishra, 2022). Another important issue is ID switching while tracking, which leads to inaccurate reference displacement and tracking deviation (Gao et al., 2022) and double counting of the fruit, which Wenli Zhang et al. (2022) solved by establishing a specific tracking region counting strategy.

Vineyard management is a very valuable task since the quality of the wine, which is a highly rewarded product, depends on all the practices that are conducted in the vineyard and the inputs that are applied. Hence, it is important to monitor grape bunch development in order to maintain healthy and productive vines (Figure 2.5). However, there are great differences between white and red varieties, which ease the detection of the latter when the bunches are ripe because of the colour distinction between the bunch and the canopy (Liu and Whitty, 2015; Torres-Sánchez et al., 2021; C. Zhang et al., 2022). Therefore, the detection and tracking of white varieties become a more demanding task. The two biggest challenges identified in the field of grape bunch detection were the occlusion of the fruit due to dense canopy (Ariza-Sentís et al., 2023a; Guadagna et al., 2023; L. Shen et al., 2023) and data scarcity, which Ciarfuglia et al. (2023) addressed training the datasets with pseudo-labels for the detection and segmentation tasks. Further, (Ariza-Sentís et al., 2023d; Santos et al., 2020) provided open-source datasets to solve data scarcity in vineyards.

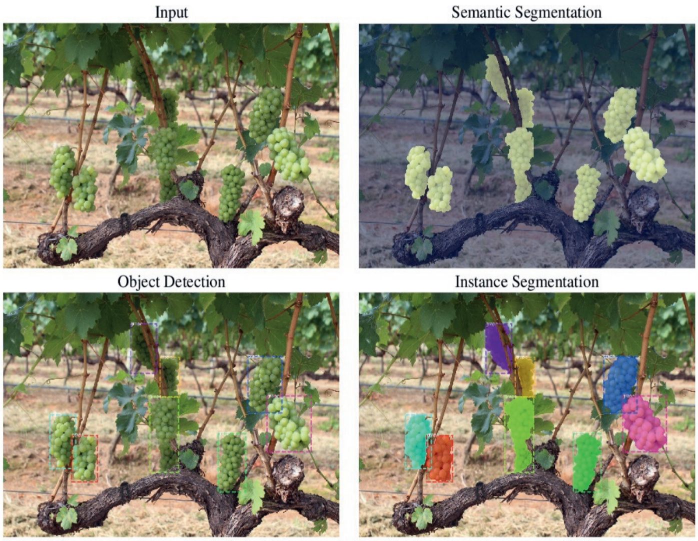


Figure 2.5. Computer Vision tasks applied to grape bunches. Source: Santos et al. (2020)

2.4.2.4 Weed detection

Weeds are known to reduce crop yield since they take resources, such as water and fertiliser, that were applied to the field for the crop but are absorbed also by weeds, lowering the remaining amount for the crop itself (Klingman and Noordhoff, 1961). Moreover, weeds in a field make the crop compete for a fundamental resource: light. Therefore, weed detection is key in precision agriculture to optimise the inputs of the crop and to apply the chemical only to the areas that have the presence of weeds, lowering the cost for the farmer and producing a more sustainable end-product (Bongiovanni and Lowenberg-Deboer, 2004).

Some studies work with RGB imagery for precise weeding, using CNN-based algorithms, such as Faster R-CNN (Khan et al., 2021), any version of YOLO (Gallo et al., 2023; Lac et al., 2022) (Figure 2.6), and InceptionV4 (Mishra et al., 2022). An advantage of working with RGB imagery is that it is convenient for the farmers since these sensors are more affordable to have on a farm. Rani et al. (2022) provided a framework that combined Histogram of Gradients (HOG) and SURF (Speeded Up Robust Feature) algorithms. It was added to a field robot, which could automatically detect weeds for various crop types and sizes and decide whether to spray weedicide. However, research should also consider multispectral sensors since they are capable of evaluating information beyond the visible spectrum, which can be key to identifying issues at an early stage.

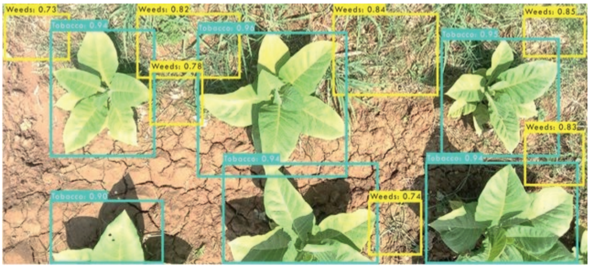


Figure 2.6. Weed detection predictions in tobacco crop using YOLOv5. Adapted from (Alam et al., 2022).

2.4.2.5 Disease and pest detection

Diseases and pests interrupt or modify the vital functions of the crops, reducing the photosynthetic rate of the plant and leading to a lower yield at the end of the campaign and economic losses for the farmer. Moreover, the end product might be contaminated by fungi (mycotoxins), bacteria, viruses, and animals such as insects, which can affect the rest of the food chain (Oliveira et al., 2014; Torres et al., 2019). Further, early identification of fungal and other microorganisms' attacks in crops can provide a proper time window to effectively apply the appropriate treatment (Vélez et al., 2023a), which can be done thanks to the development of object detection and tracking (Coulibaly et al., 2022).

Most of the research articles found regarding pest detection were identified within grain and oilseed crops, such as maize (Ishengoma et al., 2021; Sheema et al., 2021), wheat (P. Chen et al., 2021; Li et al., 2019), and soybean (Abade et al., 2022; Tetila et al., 2020; Verma et al., 2021) (Figure 2.7). The same pattern was diagnosed with disease detection, led by wheat leaf diseases (Jiang et al., 2022; Kumar and Kukreja, 2021; Lin et al., 2019; Singh and Arora, 2020; W.-H. Su et al., 2021), followed by rice (Bari et al., 2021; G. Zhou et al., 2019), and soybean (K. Zhang et al., 2021).

Figure 2.7. Soybean insect pests examples used to train the pest detection algorithm. Source: Tetila et al. (2020)

There were two big challenges found for disease and pest detection with object detection and tracking. The first consists of the lack of public datasets to train the algorithms (Čirjak et al., 2023). The second is the capacity to classify multiple diseases (Kaur et al., 2022) or pests simultaneously (Qiang and Shi, 2022; Wen et al., 2022; Wei Zhang et al., 2022) or when are in dense clusters (R. Wang et al., 2022) since most of the time, once the plant is debilitated by the presence of a pathogen or animal, it is more likely to develop more diseases or pests. Further, the developed algorithms should be able to generalise for other diseases or pests (Hong et al., 2022; Liu et al., 2022). Besides, the majority of disease and pest detection research papers were trained with CNN-based algorithms (Amrani et al., 2023; Pavithra et al., 2023; Rezk et al., 2022; Storey et al., 2022).

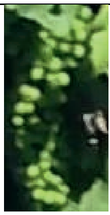
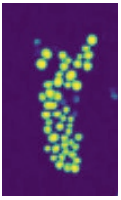
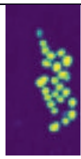
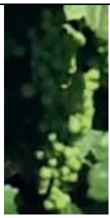
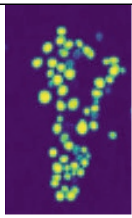
Lastly, interesting research was performed by Acharya et al. (2022)**,** where they detected and tracked droplets in images to measure their size and velocity, which provided insights into the effectiveness of spraying systems. In order to be able to apply precise spraying, the algorithm needs to offer real-time detection and tracking (Roy et al., 2022, p. 202; R. Wang et al., 2021; Y. Xu et al., 2022) and incorporate them in mobile terminals to boost agricultural productivity (Chodey and Noorullah Shariff, 2023).

2.4.2.6 Plant phenotyping

Plant phenotyping is an emerging field of study that combines multiple methodologies and protocols in order to measure and extract plant traits. The obtention of those traits is important to better understand the functioning of the crops, which can lead to an increase in yield production and a more optimised calibration of crop models and enhanced genomic selection (Heffner et al., 2009; Jannink et al., 2010). High-throughput phenotyping in precision agriculture is relevant to upgrade management practices, while producing more efficiently and reducing the invested inputs, such as fertiliser, water, and pesticide (Qiao et al., 2022).

It is of crucial importance to continue the development of phenotyping by combining it with the recent advances in technology (Mochida et al., 2019). For instance, Ariza-Sentís et al. (2023a) established a methodology to extract phenotyping traits of grape bunches and berries, such as their length, width, and shape. To do so, they first detected and tracked the grape bunches in RGB videos and afterwards, they identified berries within the detected bunches (Table 2.2). Further, Santos et al. (2020) detected and tracked grape bunches with several Computer Vision tasks, and Kierdorf et al. (2022) provided a method to estimate occluded grape berries by implementing conditional generative adversarial networks (cGAN), a variant of GAN that involves the generation of images with conditions imposed by a generator model.

Table 2.2. Grape berry counting prediction compared with the ground truth value. Adapted from Ariza-Sentís et al. (2023a).

Image crop (Ground Truth)	Spatial Embeddings prediction	Ground truth count vs prediction
		43/47
		22/23
		45/39

Nevertheless, most of the research papers devoted to phenotyping perform object detection without considering the tracking part, even if the term *tracking* is mentioned. This is due to the fact that in many cases, tracking is understood as crop monitoring, without considering the methodology used, which in most cases is monitored using time series instead of tracking inferring the Computer Vision task.

Phenotyping has shown a lot of potential in grain and oilseed crops because of their annual cycle, which allows observing the improvement made directly in the following campaign, which speeds up phenotyping tasks. Hence, most of the studies related to phenotyping are focused on continuous crops, such as maize (Kienbaum et al., 2021; Warman et al., 2021; Xiang et al., 2023; Zou et al., 2020), wheat (Furbank et al., 2019; Gong et al., 2021; J. Li et al., 2021; Sadeghi-Tehran et al., 2019), rice (Deng et al., 2021; Tan et al., 2023), soybean (S. Li et al., 2022; Liu et al., 2023; Pratama et al., 2020b; S. Yang et al., 2021), and forages (Castro et al., 2020).

The same reasoning applies to horticulture, such as lettuce (Bauer et al., 2019), strawberries (Caiwang Zheng et al., 2021), and cucumbers (Boogaard et al., 2020), which mostly breed for characteristics related to higher yield along with resistance to biotic and abiotic stresses, such as pests and diseases, drought, salinity, and sodicity (Kumar, 2006).

2.4.2.7 Livestock and other animals

The primary sector encompasses a wide range of activities, including agriculture, forestry, and fishing, object others. One area that has seen significant growth in recent years is the application of object detection and tracking technologies for animal management (Alanezi et al., 2022). The inherent nature of this sector, which involves the rearing, breeding, and overall management of livestock and wildlife, has driven this surge in interest. These advanced technologies offer a multitude of benefits, such as monitoring animal health, tracking movement, and identifying specific individuals for breeding or research purposes (Morrone et al., 2022). As a result, various solutions have been developed and implemented, improving efficiency, productivity, and overall animal welfare (Tuyttens et al., 2022). The focus on animals in the primary sector highlights the potential impact of object detection and tracking, encouraging further research and innovation to extend its application to other aspects of the sector (Yousefi et al., 2022).

Most of the studies related to object detection and tracking for livestock aim to count the number of animals that are present within the field of view of the surveillance camera (Zheng et al., 2023a) or a thermal camera (Kim and Kim, 2020), in the case of indoor animals, or construction time-lapsed camera or UAV, in the case of observing pastures . One of the direct applications of object detection and tracking is the monitoring of the animals, which allows observing certain behaviours that might be causing some illnesses, such as lameness (Zheng et al., 2023b), or for disease prevention and control (Xu et al., 2021; Zhuang and Zhang, 2019). Some studies present a general methodology with applicability to other farming animals. For instance, Haalck et al. (2023) developed a methodology to study small animal behaviour in complex environments, which provides helpful information since their gained knowledge can be applicable to other terrestrial species under realistic conditions.

The poultry industry has a lot of research on this topic, mostly for counting broilers for precision chicken management (X. Li et al., 2022) (Figure 2.8) and continuous movement monitoring on farms (Siriani et al., 2022). Also, it can be useful to compare two groups with different feeding possibilities, such as restricting and unrestricted feeding birds, and extract conclusions such as which target group walks more around the feeder, which be helpful for an optimised feeder design and resource placement (G. Li et al., 2021). The swine industry also allocates lots of resources to pig counting for efficient and low-cost farm management (Kim et al., 2022), to monitor individual activity as a measure of resilience (van der Zande et al., 2021), and to automatically identify social contacts such as head-head and head-tail contacts to enhance animal monitoring systems (Wutke et al., 2021). An interesting case study is the one presented by (Chang and Guo, 2018), where they use IP cameras to detect monkeys that damage crops and alert farmers that they are approaching the fields to prevent crop losses.

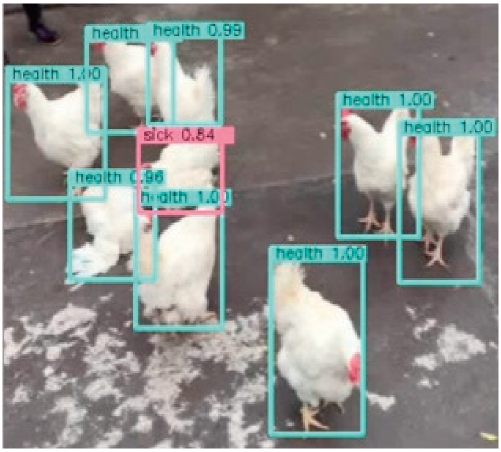


Figure 2.8. Identification of healthy and sick indoor broilers using object detection techniques. Adapted from Zhuang and Zhang (2019).

Three remarkable challenges were observed for animal detection and tracking: first, the lack of open-source datasets. To address this, Tu et al. (2022) provided a public dataset containing annotations of group-housed pigs, and (Vayssade et al., 2023) dealt with the issue by utilising an unsupervised learning method. The second identified difficulty in the sector is the placement of the camera because when animals move, certain positions are hidden from the camera, making it difficult to track them while being in an occluded location (Brunet et al., 2023; He et al., 2021; Neethirajan, 2022). The third limitation concerns the uneven distribution of the animals in the spaces covered by the camera (Zheng et al., 2023a), which leads to underestimation or overestimation of the present animals.

Lastly, H. Wang et al. (2022) performed real-time detection and tracking of abnormal behaviour in porphyry seabream while in a recirculating aquaculture system. They obtained a high tracking precision of 76.7%, which leads to improved fish welfare and increased survival rates, which consequently generates higher economic benefits of aquaculture.

2.4.3 Potential issues

Throughout this review, it has been observed that there are several limitations regarding object detection and tracking within PF. The first is the occlusion of the target, for which research suggests using multiple fields of view to be able to fully see the objective. Another challenge is the real-time processing of the data, which can be computationally challenging when implementing object detection and tracking algorithms. Real-time is relevant since many agricultural and farming applications require real-time or near-real-time feedback. Hence, it is important to consider the balance between accuracy and processing time for the specific farming case.

Another limitation is the lack of comprehensive and reliable datasets for farming applications, which are analysed in this subsection. While there are existing datasets that can be very useful (Kaggle, 2023; Roboflow Universe, 2023), they have not been published or validated through scientific methods, raising concerns about their credibility and accuracy. The absence of standardised and reliable datasets hampers the development and fine-tuning of ML models, ultimately hindering the potential for improved agricultural practices. This deficiency calls for an urgent need to establish a more rigorous approach to dataset creation, including the collection, annotation, and validation of agricultural data, ensuring the reliability and generalisability of ML models in this crucial sector. In this way, despite the small number of datasets related to agriculture or the environment in public use, some researchers have published some datasets that could potentially be useful for object detection or object detection and tracking, which are summarised in Table 2.3. Nonetheless, it is important to have diverse and representative datasets, for instance, from several geographical locations or seasons in order to generalise well and be able to apply the developed algorithm to other conditions. It can be observed that there are datasets older than 5 years as filtered in the Methodology section. However, to expand knowledge, all the public datasets found have been included in this research.

Table 2.3. Public datasets regarding object detection and tracking within the field of precision farming.

Study	Purpose of annotation	Crop / Animal	Type of multimedia	Number of annotations	Type of camera
(Nilsback and Zisserman, 2006)	Flower classification	17 species	Images	1360	Several types of cameras
(Kragh et al., 2017)	Obstacle Detection	NA	Images and videos	Not mentioned	Several types of cameras
(Hou et al., 2017)	Vegetable and fruit classification	292 classes	Images	~160000	Several types of cameras
(Pezzementi et al., 2018)	Pedestrian detection in apple and orange orchards	NA	Videos	~95000	Camera
(Van Horn et al., 2018)	Species Detection and Classification	5000 species of plants and animals	Images	~6.6 M	Several types of cameras
(Wu et al., 2019)	Pest detection	103 species	Images	18983 images	Internet images (several types of cameras)
(Zheng et al., 2019)	Species Detection and Classification	31 species of plants	Images	~49000	Several types of cameras
(Santos et al., 2020)	Object detection and instance segmentation	5 grape varieties	Images	4432 boxes, 2020 masks	Proximal sensing camera
(Sudars et al., 2020)	Robotic Computer Vision control	Food crops and weed	Images	7853	Several types of cameras
(Häni et al., 2020a)	Fruit detection, segmentation, counting	Apple	Videos	~41000	Cell phone camera
(Gené-Mola et al., 2020)	Fruit detection	Apple	Images	1455	Camera
(Tu et al., 2022)	Behaviour recognition	Pigs	Videos	8047	Overhead camera

(R. Wang et al., 2021)	Pest detection	Wheat, rice, corn, rapeseed	Images	~264700	Camera
(de Jong et al., 2022)	Fruit detection and tracking	Apple	Videos	~86000	UAV camera
(Mignoni et al., 2022)	Pest detection	Soybean	Images	6410 images	Several types of cameras
(EL Amraoui et al., 2022)	Disease detection, tree counting, classification, and segmentation	Avocado	Images	93 images	UAV camera
(D. Li et al., 2022)	Fish face identification	Golden crucian carp	Images	1160 standard box 1160 rotating box	Camera
(Giakoumoglou et al., 2023a)	Grey mould detection	Cucumber	Images	121 images	Camera
(Ariza-Sentís et al., 2023d)	Fruit detection and tracking	Grape	Videos	~8000	UAV camera
(Güldenring et al., 2023)	Grassland detection for agricultural robotics	Grassland	Images	15519	Ground robot camera

In any case, the number of datasets strictly related to farming is very limited, and the accessibility of these datasets is often restricted and they are not publicly available since it is available upon request or the links are no longer active (Giakoumoglou et al., 2023a; D. Li et al., 2022; Nilsback and Zisserman, 2006; Pezzementi et al., 2018; Tu et al., 2022; R. Wang et al., 2021; Zheng et al., 2019) (accessed on April 10th, 2023).

2.5 Discussion

In recent years, mostly from 2015 onwards (Figure 2.1), there has been a growing interest in the application of Computer Vision and DL techniques regarding object detection and tracking for farming purposes. The main reason to explain the hike in research papers devoted to this field can be the advances and availability of technology that is able to carry out precise and accurate detection and tracking of agricultural and farming objects. Nonetheless, it is important to remark that, since the world population is increasing (United Nations Department of Economic and Social Affairs, Population Division, 2022), there is a rising interest in increasing crop yield, reducing waste, and optimising resource allocation (Adli et al., 2023; Matese and Di Gennaro, 2015) to be able to feed everyone. Consequently, it is important to deeply analyse the advantages, challenges and future work that research in the field of object detection and tracking will have to face in the coming years to be able to reach the second Sustainable Development Goal set for 2030: Zero Hunger (United Nations, 2015b) along with reducing the environmental impact of the farming practices to produce food in a more green and sustainable way. However, DL and CNNs are not the unique solution for object detection and tracking. For instance, Vision Transformers (ViTs) have already been implemented for plant disease detection (Gole et al., 2023; Parez et al., 2023).

2.5.1 Advantages of object detection and tracking

The increasing interest in object detection and tracking within the field of precision agriculture and precision farming, along with the high detection and tracking metrics obtained, indicate that these technologies are suitable for several applications, such as fruit and animal counting and monitoring (Kim et al., 2022; Rong et al., 2023), diseases (Zheng et al., 2023b), weeds (Mishra et al., 2022), and pest detection (Ishengoma et al., 2021), and phenotyping purposes (Z. Li et al., 2020; Mochida et al., 2019). Further, object detection and tracking allow researchers to take advantage of useful new technologies, such as UAVs and new sensors, and expand their potential within the field of Computer Vision. Moreover, object detection and tracking permit accurate monitoring and inspection of the identified items, which can assist logistics and the supply chain. For instance,to keep track of each individual fruit/animal when carrying out monitoring and/or inspecting.

The field of precision agriculture has benefited a lot from these advances since, for instance, disease inspections in the field have always been performed through visual surveys, which are tedious tasks, time-consuming (Rahaman et al., 2015), and subjective to the operator on charge. Hence, all these improvements permit carrying out field inspections in a more objective way and most importantly, saving a lot of time for the farm manager, which allows them to apply the required chemical only to the plants that need it and within the most optimal time-window for chemical effectiveness (Ariza-Sentís et al., 2023a), which reduces the environmental impact of agriculture. Moreover, it benefits from the potential of edge computing since the developed models can be applied to edge devices, like as tractors or UAVs, which can reduce the need for data transmission and provide faster feedback. Furthermore, there is a need to establish automated pipelines and workflows in order to avoid human errors and reduce the waiting time between processes, and object detection and tracking have the potential to provide insights into that topic.

Another advantage of object detection and tracking in PF is domain adaptation, that is, the fact that the knowledge gained in a very specific field and the models and algorithms trained for that specific use case can be straightforwardly or with few minor modifications applied to other similar scenarios, through transfer learning (Talukdar et al., 2018; Torrey and Shavlik, 2010). For instance, several fruits have a similar shape and circularity, such as peaches, citrus, apples, and mangoes. Therefore, a model can be developed to detect a particular fruit or several fruits (Chen et al., 2017; He et al., 2022) or directly be developed for a more general purpose: fruit detection and counting (Rahnemoonfar and Sheppard, 2017). However, domain adaptation can also be generalised to cross-domain collaboration and innovation, meaning that advancements done in other fields of study that have traditionally employed object detection and tracking techniques, for instance, intelligent transportation and security monitoring, can be applied to the farming domain to promote further development.

Lastly, there have already been advancements in 3D MOT technology (Pang et al., 2023; Weng et al., 2020), which showcases the promising potential for precise monitoring and analysis of various elements. For instance, it allows for accurate tracking of crops (Benet and Lenain, 2017) and livestock growth and calculation of volume variables such as the canopy volume and the animal volume, which can give insights into their development at several growing stages. Further, it leads to the usage of new sensors, such as LiDAR.

2.5.2 Challenges and future work of object detection and tracking

One of the biggest challenges of object detection and tracking is the presence of shadows in their datasets, which obscure the objects of interest and affect their appearance and hence their detection by the algorithm (Zhao et al., 2020). This difficulty has mostly been identified when trying to distinguish between weeds and crops (Dyrmann et al., 2017, 2016). This problem is particularly important when the datasets contain aerial images and videos, for instance, acquired by UAVs since they are often affected by cloud cover, haze, and adverse atmospheric distortions (Porikli, 2006). In order to solve that problem, pre-processing techniques such as contrast enhancement (Pal et al., 2021) and denoising (B. et al., 2019) are often used to improve the quality of the imagery and make them more suitable for detection and tracking.

Another difficulty is that agricultural and farming environments need to detect and track a great variety of objects (Kaur et al., 2022), such as the crop or livestock animal itself, surrounding animals, multiple weeds, diseases, and pests within the same image/video. Further, these objects are homogeneous and can be present in different shapes (Nilsback and Zisserman, 2006), sizes (Bonneau et al., 2020), colours (Xu and Mishra, 2022), and textures (Chodey and Noorullah Shariff, 2023), which hinders the task of developing a unique and robust algorithm which is able to accurately detect and track all those objects for agricultural purposes, compared to car and people detection. Moreover, those objects might suffer from being partially occluded and challenging illumination conditions (Ariza-Sentís et al., 2023a), such as the colour similarity between the fruit and the surrounding canopy (Bargoti and Underwood, 2017a; Chen et al., 2017), which can burden a lot of the task of fruit counting, with fruit under- or overestimation.

The necessity of large datasets for training algorithms and avoiding overfitting in object detection and tracking presents a significant disadvantage in the field of Computer Vision (Pal et al., 2021). Acquiring, annotating, and storing such extensive datasets can be resource-intensive and time-consuming. Before applying Computer Vision algorithms for object detection and tracking in agriculture, it is crucial to ensure that the image data is appropriate for analysis (Katal et al., 2013) and that the data along with the annotations have sufficient quality and accuracy for the final application since it can already be a limiting variable to reach high detection and tracking metrics. This is especially important in agriculture due to the complex and dynamic nature of the farming environment. Unlike other fields where object detection and tracking are applied, agriculture and farming involve living organisms, varied landscapes, and unpredictable weather conditions. Furthermore, the detection and tracking of farming targets require a more comprehensive approach that takes into account the biophysical characteristics of the crops, animals, pests, and other organisms present in the ecosystem. For example, the use of visible light (RGB) cameras might not be adequate for the detection of certain diseases that affect crops, such as powdery mildew. Instead, multispectral and hyperspectral imaging techniques may be required to capture the subtle differences in reflectance that are indicative of the presence of the disease (Abdulridha et al., 2020; Kuska et al., 2018). Another example could be to detect livestock diseases, for which it might be more suitable to use thermal cameras (Tzanidakis et al., 2021; Zheng et al., 2022), similarly, thermal data has also been utilised as a tool for assessing water stress in plants (Buunk et al., 2023; Gonzalez-Dugo et al., 2019; Katimbo et al., 2022). Hence, it is important to remark that multimodal data, collected from different platforms and sensors can provide more comprehensive information to better support PF applications.

It has been mentioned in this review and by other authors that there is a lack of public datasets regarding object detection and tracking (Akbari et al., 2021), and as observed in Table 2.3, most of them only deal with object detection, leaving object tracking with very few open-source datasets. Furthermore, data collection is time-consuming, expensive, and might be even prohibited by law in very specific environments (Kiefer et al., 2021), such as flying UAVs close to an airport or being inside a natural park. However, synthetic data is faster, more flexible, cheaper, and has cutting-edge privacy compared to real data. Several authors have already benefited from synthetic data in order to train ML and object detection algorithms (Akyon et al., 2021; Giakoumoglou et al., 2023b), for which the scalability was tested by performing a similarity assessment between the real and synthetic data (Klein et al., 2023). GANs have already been implemented within the farming domain (Lu et al., 2022). However, those models are prone to instability problems (Arjovsky and Bottou, 2017; Goodfellow et al., 2020) and it is still challenging to train the models to generate meaningful images that can benefit the purpose for which they were created (Zhu et al., 2020) since the number of public training images available is low (Brock et al., 2019).

Another alternative is image augmentation techniques (Wu, 2011), such as flipping, rotation, and scaling, which can be used to increase the amount of data available for training and testing. This helps to prevent overfitting and improve the performance of the model (D. Su et al., 2021). Moreover, there is a problem of data imbalance with certain classes in agricultural datasets, like a specific disease or pest, which can be underrepresented and lead to lower performance of the detection and tracking models. Additionally, it is important to consider the quality of the image data, including factors such as resolution and noise, as this can impact the performance of the algorithm. Overall, careful pre-processing of the image data is essential for achieving accurate and reliable object detection and tracking in agriculture (Cap et al., 2022; Shorten and Khoshgoftaar, 2019).

In addition to these challenges, it is important to remark on the need for appropriate and efficient hardware (X. Zhang et al., 2020) and software infrastructure for object detection and tracking, which might require substantial computational power and storage data, which can be a limiting factor for farmers in resource-limited settings. It is relevant to remark that contrary to other domains, agricultural hardware is exposed to real-world settings, such as mud, dust, rain, and chemicals, among others, which should be considered when selecting the appropriate hardware to be present in the field. For that, it is relevant to select the opportune sensors (Pádua et al., 2017), such as RGB, multispectral, thermal cameras or LiDAR, and the convenient platform from which the dataset will be acquired, which can be UAVs, ground robots, and tripods, among others. Furthermore, it is important to determine the appropriate algorithm (Naeem et al., 2013), such as Faster R-CNN, any version of YOLO, or Deep SORT, for object detection and tracking, and to ensure that they are optimised for the specific task at hand. Furthermore, it is also key to select the appropriate technology for which the algorithm will be integrated, for instance, with Internet of Things (IoT) devices (J. Xu et al., 2022).

It is important to remark that, even if object detection and tracking have shown a lot of potential and good detection and tracking accuracies, they face some difficulties and limitations, for instance, their applicability and method-acquisition by the farmers, who are the main stakeholders and for which research should target their applications (Snapp et al., 2003). Hence, research must consider which are the current challenges that should be solved to make them more affordable and attractive for the end user. A relevant point here is that the centre of attention is meant to be the Computer Vision task, but not the acquisition of the data and its optimisation (Ariza-Sentís et al., 2023a; Mazumder et al., 2023), which might influence the quality of the collected data and might help to increase the metrics obtained. For instance, despite the importance of pre-processing image data, many studies in the field of Computer Vision and object detection in agriculture often overlook the appropriate methods for acquiring the images. For example, capturing images at a good angle to avoid ID switching while tracking, optimal altitude and camera angle, flying or walking path, or implementing other pre-processing methodologies such as image-stitching prior to object detection (Y. Zhou et al., 2019), can be crucial for obtaining high-quality images that contain relevant information about the objects of interest.

For that, it is important to carefully design and plan the path that needs to be followed by the platform to collect the datasets in the most optimal way. In that sense, path planning can play a crucial role since it consists of designing the most appropriate route from the initial point to the endpoint, considering and avoiding the obstacles found on the way, for instance, trees (Gasparetto et al., 2015), transmission towers, and terrain slope. Moreover, the optimisation of the route is crucial for the platforms, mostly UAVs, since they face low autonomy, for which the data acquisition should be carried out within the minimum amount of time (Aggarwal and Kumar, 2020; Oksanen and Visala, 2009). Failure to consider these factors can lead to low-quality images that are difficult to analyse, which can impact the performance of the algorithm. Moreover, it is important to mention the importance of interpretability in DL models to not only obtain a result, for instance, a disease prediction but also to understand the reason behind the model detecting that particular issue, especially when it comes to Decision Support Systems (DSS) for disease detection. Therefore, it is important to emphasise the need for appropriate image acquisition methods and to encourage researchers to consider these factors when designing experiments or collecting data. By doing so, we can ensure that the image data used for object detection and tracking in agriculture is of high quality and suitable for analysis, leading to more accurate and reliable results.

Lastly, it is important to remark that, even if the integration of object detection and tracking has shown substantial benefits for PF, such as optimisation of resource allocation and enhancement of animal welfare, the implementation of such systems may face barriers often overlooked. Factors like limited connectivity in rural areas, insufficient digital literacy among farmers, and uncertainties regarding return on investment can present major challenges for the field. The mere presence of technological advantages does not guarantee its widespread adoption. Therefore, it is relevant to address these barriers and ensure accessibility, education, and clear demonstration of long-term benefits to foster the adoption of these technologies by farmers.

2.6 Conclusions

This paper undertook a comprehensive review of object detection and tracking within the frame of PF, for which over 300 research articles were examined and the particular field of study, the algorithms used, the metrics obtained, the difficulties and limitations faced, and the availability of public datasets, were evaluated. The purpose of this review was to solve the two main research questions while providing an analysis of how Computer Vision and DL techniques can be optimised to maximise their impact within PF and presenting a detailed overview of the current advancements in object detection and tracking techniques and applications, showing the advantages and limitations to encourage more researchers to experiment with object detection and tracking for farming functionalities and to motivate them to make their datasets open-source. This open-source approach can save the scientific community from the time-intensive task of manual annotation with each new DL project.

Our findings suggest that while object detection and tracking can be applied to any crop, having ample revenue facilitates its implementation due to the investment required in modern technology. Nevertheless, object detection and tracking is a promising area of research that holds potential for revolutionising crop and livestock management while optimising resource allocation, paving the way for the robotisation of the farming sector.

The future of object detection and tracking lies in overcoming the difficulties analysed in this review, for instance, target occlusion because of camera altitude, angle, leaf density, or crowded scenarios. A proposed solution to that problem is to plan optimal data acquisition before actually acquiring the data and to implement multiple-angle viewing systems to observe the target from multiple points of view to be able to properly detect and mostly track the object in its full size. Furthermore, it would be beneficial to emphasise the significance of model interpretability within agricultural contexts. Discerning the rationale behind a model's decision is imperative for establishing trust among farmers and ensuring adherence to regulatory standards. Additionally, the integration of diverse data sources, including but not limited to thermal, lidar, multispectral, and hyperspectral sensors, in conjunction with object detection and tracking techniques has the potential to revolutionise the food production sector. Such integration has the potential to facilitate a holistic understanding of the agricultural landscape.

Directions for Future Research:

1) Shifting the emphasis from object detection and tracking algorithms and metrics towards optimal data acquisition.

2) Incorporating prior knowledge of the biophysical environment to design optimal path planning.

3) Adopting multiple points of view and angles to circumvent object occlusion.

4) Releasing additional open-source labelled datasets.

5) Leveraging synthetic data generation techniques to supplement limited real-world datasets.

6) Designing efficient and robust hardware setups suitable for agricultural environments, which are often harsher than other scenarios, considering factors like durability, adaptability, and real-world exposure.

7) Addressing barriers to widespread adoption of these technologies in agriculture, including connectivity issues, lack of digital literacy, and uncertainties regarding return on investment.

8) Emphasising interpretability of object detection and tracking models to boost agricultural DSS.

Chapter 3

Two-phase framework and comparative analysis of UAVs, UGVs, and tractors for precision farming. Use case: spraying

This chapter is based on:

Ariza-Sentís, M., Mier, G., Vélez, S., Valente, J., 2024. Comparative Analysis of UAVs, UGVs and Tractors for Precision Spraying in Vineyards: Addressing Economic, Energy, and Sustainability Aspects. Computers and Electronics in Agriculture [under review]

Ariza-Sentís, M., Vélez, S., Valente, J., 2023. BBR: An open-source standard workflow based on biophysical crop parameters for automatic Botrytis cinerea assessment in vineyards. SoftwareX 24, 101542. https://doi.org/10.1016/j.softx.2023.101542

Abstract

The intensive use of pesticides has raised concerns about the collateral damage to non-targeted species and soil health degradation. Hence, research must focus on lowering chemical usage through accurate phytosanitary applications. The proposed approach utilises a two-phase framework to assess the presence of Botrytis Bunch Rot through i) a general overview of the vineyard which considers the biophysical variables of the field and generates a disease risk map, and ii) a closer view of the vine plants to accurately plan aerial routes for accurate inspection and chemical application only to infested plants. The results indicate that the first flight allowed the production of heatmaps with acceptable accuracy ($R2 > 0.7$). Further, the accurate spraying minimised overall pesticide use and lowered environmental impact by up to 78%. When there was a localised focus on infection, UAVs showed up to 41% less distance travelled compared to tractors and ground robots, and up to 38% less spraying time compared to ground robots, translating into a more environmentally sustainable method by reducing energy consumption and battery usage. In the case that there was a widespread outcome of Botrytis in the vineyard, UAVs became less competitive, with a spraying time 150% greater than ground robots, and 291% higher than a tractor due to battery constraints. UAVs offered the cheapest options for all levels of risk until 19 hectares when UGVs become cheaper for low-risk cases. After 9 and 5 ha, UGVs also become cheaper than UAVs for medium and high-risk scenarios, whereas tractors become more competitive than UAVs after 6.5 hectares for high-risk areas. Future research should address not only battery constraints but also tank capacity limitations. In addition, it would consider the volume of chemicals applied per plant, attending farmers' socio-economic implications and adoption challenges for widespread implementation in agriculture.

3.1 Introduction

The intensive use of pesticides has profound consequences on the environment (Carvalho, 2017), resulting in collateral damage to non-targeted species, including crop-beneficial insects, birds (Fry, 1995), and aquatic organisms (Shefali et al., 2020). Furthermore, the persistence of phytosanitary residues in the soil and water aggravates environmental degradation, compromising long-term sustainability and soil health (Baweja et al., 2020; Lechenet et al., 2014). Nevertheless, the abstention from using chemicals on crops can lead to escalating vulnerability of agricultural systems to pests, causing quality and yield reduction (Oerke, 2006), which is unsustainable given the continuous increase in population that needs to be fed (United Nations Department of Economic and Social Affairs, 2022). Consequently, it is of crucial importance to reduce the amount of pesticides and execute precise applications only on infested plants (Bongiovanni and Lowenberg-Deboer, 2004) without prohibiting their usage to enhance sustainable production. Precise chemical application reduces the amount of phytosanitary sprayed over the whole field, which translates into a reduction of expenses from the farmers' side and, therefore, a higher revenue (Tona et al., 2018). Moreover, the final product is of higher quality and can be sold at a higher price or used to enhance the marketing of the product (Verhaegen and Van Huylenbroeck, 2001).

Disease detection has traditionally been carried out by field experts. However, it presents a time challenge since extensive areas must be surveyed within limited timeframes, balancing the brief interval between the initial appearance of symptoms and the optimal moment of action of the phytosanitary (Tang et al., 2010). In recent years, much attention has been focused on disease and weed detection using ML and DL algorithms (Ariza-Sentís et al., 2024b; Shruthi et al., 2019; Vijayakumar et al., 2023). In that sense, AI has provided new tools to detect diseases at the very initial stages of development since their predictions are based on pattern recognition (Burr, 2008). Nevertheless, those patterns can be recognised when their effects are located on visible parts of the plant, such as the canopy since the spectral signature changes, which can also be identified using vegetation indexes (Al-Saddik et al., 2017; Kumar et al., 2016). In the case of vineyards, some diseases start growing inside the grape bunches, being invisible to the human eye and without modifying the spectral signature of the vine, for instance, Botrytis Bunch Rot (BBR), which is caused by the fungus *Botrytis cinerea*. To prevent significant quality and yield losses, addressing diseases in vineyards before symptoms become visible is crucial. By this stage, the disease is often advanced, and the effectiveness of phytosanitary products markedly decreases. Thus, focusing on the assessment of risk factors for early detection and prevention of diseases is essential, rather than waiting for visible signs of infection.

In this regard, a different approach involves evaluating the probability of disease occurrence by considering biophysical field conditions, which avoids dependence on symptom manifestation and predicts the areas with the highest probability of disease development. For instance, (Vélez et al., 2023a) assessed the presence of BBR UAV multispectral imagery by considering biophysical parameters, reaching an accuracy of $R^2 > 0.7$ compared to ground truth data.

UAVs have successfully been researched to assist in spraying in agricultural fields (Hafeez et al., 2023; Velusamy et al., 2022). Nevertheless, limitations in detecting hotspots and the simultaneous application of chemicals have been reported due to the limited battery life, which is one of the most important limiting factors in UAV spraying (Cavalaris, 2023) and provides a big disadvantage compared to other spraying methods, such as tractor sprayers. Therefore, it becomes crucial to focus on resource limitation optimisation for UAVs in order to spray larger zones.

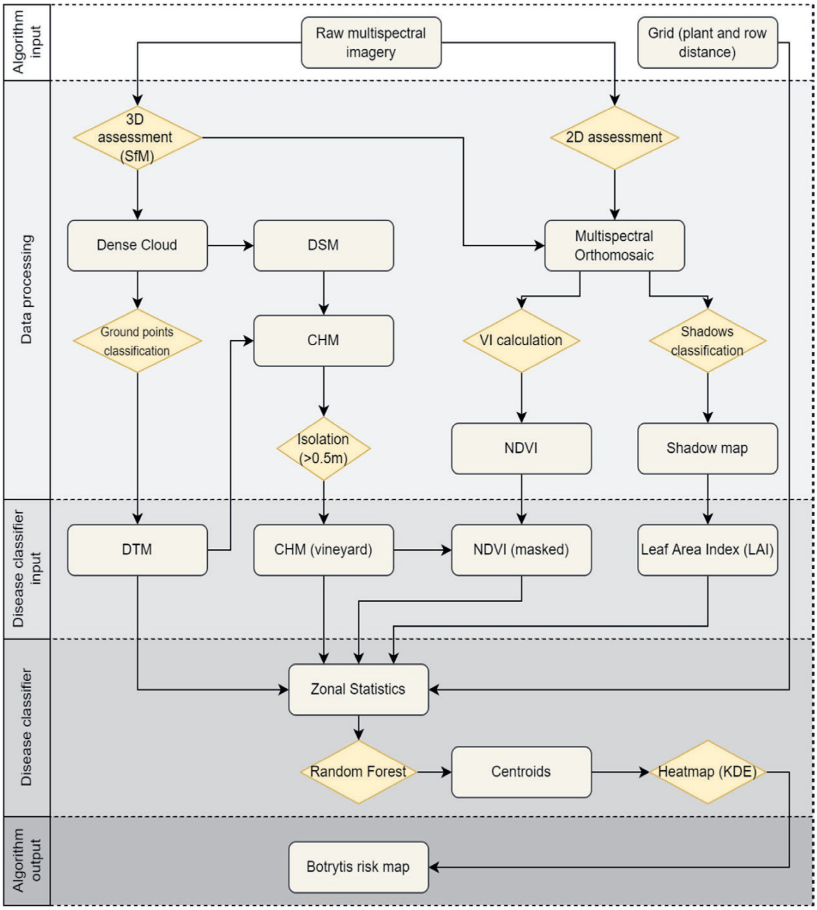
UAV path planning has been implemented in agriculture (Basiri et al., 2022; Jeon et al., 2024; Mukhamediev et al., 2023; Shi et al., 2023) and combined with pesticide spraying (Becce et al., 2021; Guo et al., 2021; J. Li et al., 2023; Pham et al., 2020). Accurate application of the targets is one of the most significant advantages of spraying UAVs. Nevertheless, most of the research focuses on Coverage Path Planning (CPP), which implies flying over all the vine plants and applying chemicals to the whole field. In order to enhance precision agriculture, phytosanitary measures should only be applied to infected plants. Furthermore, in the case of crops trained in a vertical trellis system, such as vineyards, it is relevant to consider both sides of the canopy, which has not been taken into account in previous aerial CPP approaches. Moreover, unlike what is often done for research purposes (Nuske et al., 2014; Rose et al., 2016; Santos et al., 2020; L. Shen et al., 2023), commercial vineyards do not always undergo leaf removal as a common practice, which means that grape bunches are often occluded behind a branch or a leaf. Hence, in order to properly apply the chemical, the algorithm should consider multiple points of view to spray the largest visible part of the bunch. Lastly, the specific biophysical conditions of the field are not considered, which is crucial in agriculture since plants are in continuous development and require targeted route optimisation depending on their growth stage.

Path planning has already been developed for unmanned agricultural vehicles to carry out several tasks, for instance, precise chemical application with UGVs (Chakraborty et al., 2022; Gonzalez-de-Santos et al., 2017; Nanavati et al., 2023; Xu et al., 2023). However, one relevant advantage of UAVs over UGVs is their ability to execute interrow movements to change the canopy side by flying over it. This particularity, which is also applicable to UAVs over tractors, shows the potential to reduce the overall time and distance travelled by the UAV compared to other platforms since UGVs and tractors need to follow the row from the beginning to the end to spray.

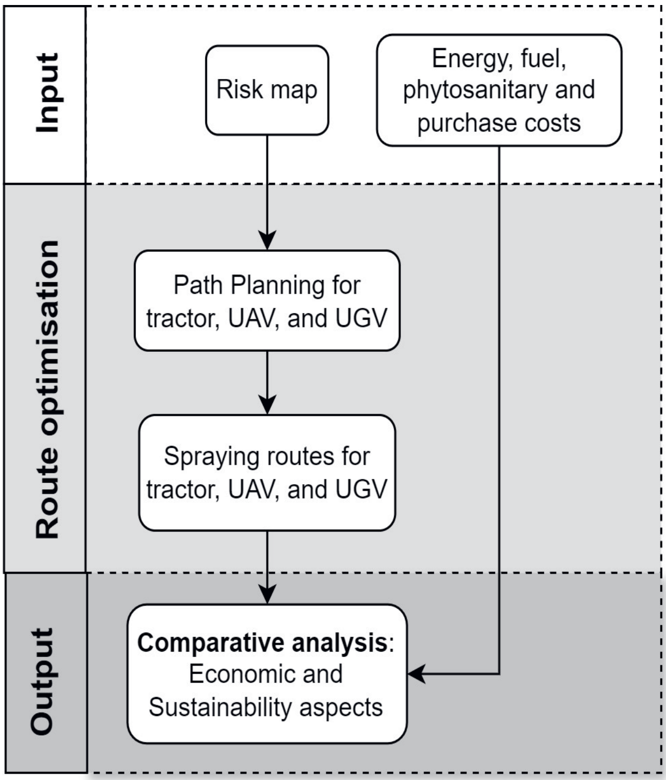
Finally, similar to (Matese et al., 2015), who studied the difference in performing Normalised Difference Vegetation Index (NDVI) surveys with UAV, aircraft, and satellite to represent the spatial variability of the vineyard, and (Martinez-Guanter et al., 2020), where they compared the application cost of several platforms, including UAVs for olive and citrus orchards, it is relevant to develop the economic analysis and the costs of implementing and carrying out precision spraying in vineyards with different levels of infection with multiple pieces of equipment. (Morales-Rodríguez et al., 2022) concluded that a large investment is necessary to acquire a UAV sprayer, whereas the operating costs are lower than for conventional sprayers. Moreover, UAVs require less water and phytosanitary costs. Nevertheless, they concluded that various factors might render traditional sprayers a more favourable option. Therefore, this paper aims to assess the feasibility of UAVs, UGVs, and tractors spraying in vineyards with increasing levels of BBR disease affection by comparing the economic, energetic, and sustainability aspects considering battery constraints.

3.2 Materials and Methods

The workstream that was followed in this research is depicted in Figure 3.1a,b. It consists of the acquisition of field knowledge based on the current biophysical variables of the field to generate a disease risk map, and the consequent optimisation of resources to spray the areas with potential of developing the disease with the least time required.


Algorithm input
Data processing
Disease classifier input
Disease classifier
Algorithm output
Raw multispectral imagery
Grid (plant and row distance)
3D assessment (SfM)
2D assessment
Dense Cloud
DSM
Multispectral Orthomosaic
Ground points classification
CHM
VI calculation
Shadows classification
Isolation (>0.5m)
NDVI
Shadow map
DTM
CHM (vineyard)
NDVI (masked)
Leaf Area Index (LAI)
Zonal Statistics
Random Forest
Centroids
Heatmap (KDE)
Botrytis risk map

(a)



(b)

Figure 3.1. Workflow of the methodology to obtain the optimised route(s) for precise spraying in vineyards. Figure 3.1a depicts the process of disease assessment from raw UAV multispectral images. Figure 3.1b indicates the workflow to obtain the optimised spraying routes along with a comparative analysis between platforms.

3.2.1 Risk map: botrytis bunch rot assessment

The BBR assessment (Figure 3.1a) starts with the acquisition of raw multispectral imagery with a UAV. This data is processed to generate several maps, such as the Digital Terrain Model (DTM), the Canopy Height Model (CHM), the NDVI, and the Leaf Area Index (LAI) as extracted by (Vélez et al., 2021). The CHM, considering only the values between 0.5 and 2 meters in height, is used to crop the NDVI map to the exact extent of the vineyard plants and avoid inter-row vegetation bias. Those maps are then used to train a Random Forest algorithm to predict the likelihood of developing BBR disease. The Random Forest is trained with 500 trees and a split ratio of 0.75. Afterwards, the trained algorithm is used to produce a disease risk map based on the current biophysical conditions of the vineyard, as introduced by (Vélez et al., 2023a) and automatised by (Ariza-Sentís et al., 2023c). This heatmap is further used to generate the spraying routes according to the threshold above which the pesticide should be applied (Figure 3.2).

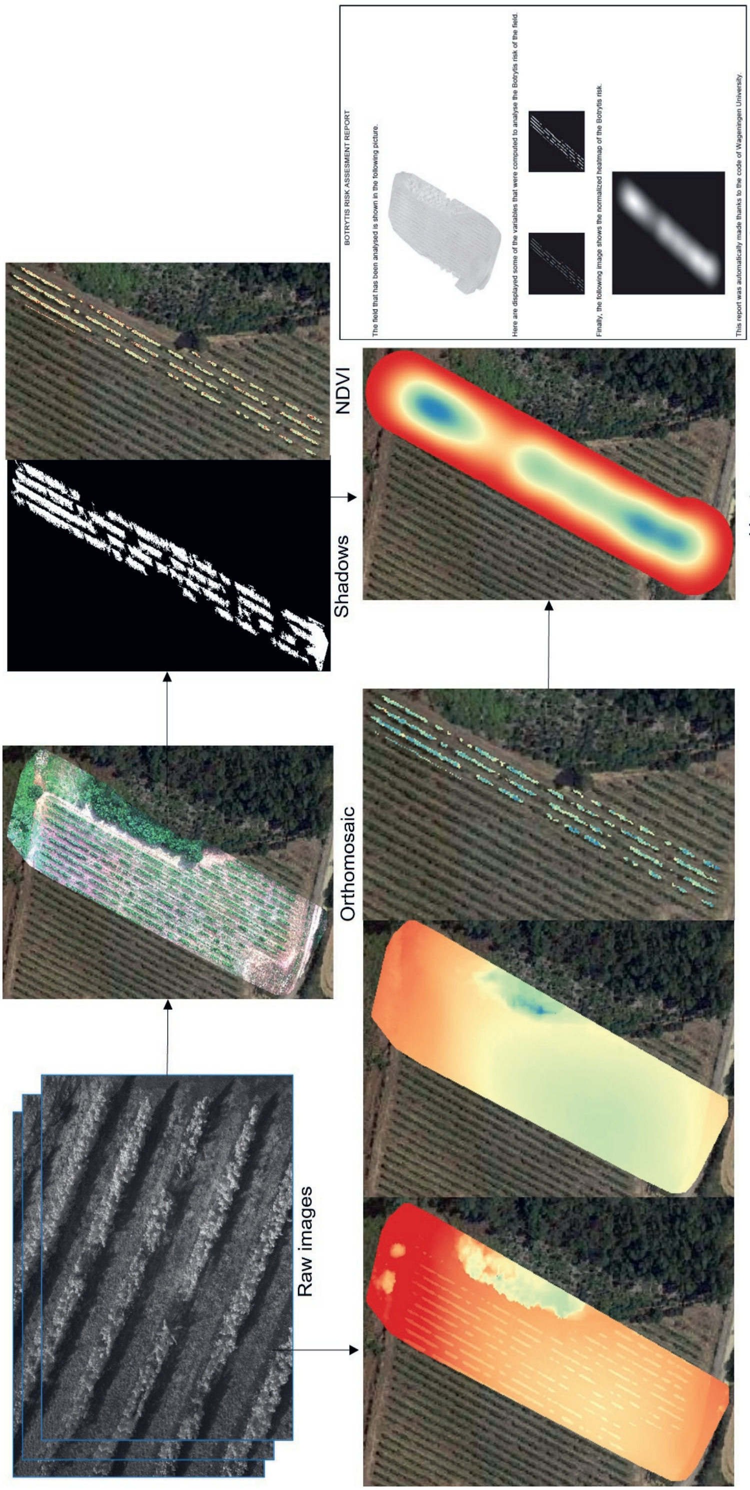


Figure 3.2. Input (top left), middle-products (top and bottom middle), and outputs (bottom right) of the BBR software. To generate the heatmap and the assessment report, the shadows, the NDVI, the DTM, and the CHM are used to train the Random Forest algorithm.

3.2.2 UAV path planning

The risk map indicates the likelihood of developing the BBR disease. The map is divided using a grid into smaller cells. The distance between two cells in the same row is defined as the distance between plants and each plant is represented in two cells, one for each side of the canopy. Those cells are considered to be sprayed by the UAV.

The UAV needs a route that optimises the spraying task. This can be modelled as the Vehicle Routing Problem (VRP) (Dantzig and Ramser, 1959; Toth and Vigo, 2002). The VRP is a known optimisation problem that consists of finding the route that minimises a given cost function while visiting all the nodes exactly once and returning to the origin node with one vehicle. Its formulation consists of the following equations:

$$\min \sum_{\mathrm{i} \in \mathrm{V}} \sum_{j \in V} c_{ij} x_{ij} \tag{1}$$

subject to:

$$\sum_{i \in V} x_{ij} = 1 \; \forall j \in V \backslash \{0\} \tag{2}$$

$$\sum_{j \in V} x_{ij} = 1 \; \forall i \in V \backslash \{0\} \tag{3}$$

where c_{ij} is the cost of the economic, energy, and sustainable aspects of t of going from node i to j and x_{ij} a binary variable to decide whether the vehicle moves from i to j, and V is the list of nodes. Hence, it is ensured that each node is visited just once.

In the case of the spraying UAV, each node is a cell with a risk of developing BBR disease higher than α, to filter low-risk cells. The cost function for this task (Equation 4) is tailored to account for the time required to spray a plant and to change canopy side or row. The cost function is defined as:

$$c_{ij} = D_{ij} + S_{ij} \tag{4}$$

being c_{ij} the cost of going from cell i to cell j; D_{ij} (m) is the Euclidian distance in 2D between cells i and j; S_{ij} (m) is the extra cost of jumping the canopy, which is defined as:

$$S_{ij} = \begin{cases} 2\ (\mathrm{FAS} - \mathrm{FIS}) & \text{if cells } i \text{ and } j \text{ are not in the same row} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where:

FAS (m) is the fly height above the canopy and FIS (m) is the fly height in swath or spraying height. Both FAS and FIS are absolute values compared to the ground height.

In the case that cells i and j are not located in the same vineyard row (Figure 3.3), S_{ij} is the distance required by the UAV to be located above the canopy, change side, and lower again to the spraying height of the other row.

Figure 3.3. Spraying UAV over the vineyard field. To fly between two cells in the same row, the UAV flies at the same height (straight red arrow), whereas when both cells are in different rows, the UAV jumps over the canopy (half-circular red arrow).

Since UAVs have limited batteries, it is necessary to consider that limitation for route planning. This means that the UAV may run out of battery before having sprayed all cells. To solve that, it is important to model the amount of time that the UAV takes to spray each plant. Furthermore, it should be considered that the route includes a three-angle perspective in each sprayed spot to avoid grape bunch occlusion and be able to apply the chemical to the bunches in their full size, as introduced by (Ariza-Sentís et al., 2024a):

$$t_{ij} = ST_j + (D_{ij} + S_{ij})/v \tag{6}$$

being t the time that the UAV needs to travel from the cell i to cell j, and spray cell j.

The optimisation problem includes the following restrictions:

$$\sum_{i,j} t_{ij} * x_{ij} < B \tag{7}$$

where B is the battery life of the UAV.

Moreover, a penalisation for each non-sprayed cell is added to the cost of the path (Sum of the cost of visiting cells, Equation 4). This penalisation is proportional to the probability of developing the Botrytis disease to the power of 4, multiplied by a high value that prevents the optimiser from dropping nodes if it is not required. The probability of Botrytis is powered to 4 to further prioritise cells with higher risks.

Unfortunately, a lot of cells with a high probability of developing the disease cannot be sprayed due to the battery life limitation. This requires using the UAV in multiple sessions covering different cells. For that, the current problem is modelled with the multiple Vehicle Routing Problem (mVRP), where each vehicle represents a session to apply pesticide. The mVRP has the following equations:

$$\sum_{i \in V \backslash \{0\}} x_{i0} = K \tag{8}$$

$$\sum_{j \in V \backslash \{0\}} x_{0j} = K \tag{9}$$

$$\sum_{i \notin S} \sum_{j \notin V} x_{ij} \geq r(S),\ \forall S \subseteq V \backslash \{0\}, S = \emptyset \tag{10}$$

$$x_{ij} \in \{0,1\}\ \forall i, j \in V \tag{11}$$

where K is the number of available vehicles and r(S) is the minimum number of vehicles required to solve set S. $\emptyset$ is assumed to be the depot point.

The cost function and the battery life limitation used are the same as in the cases of a single vehicle.

Solving this problem is NP-hard (Tindell et al., 1992), but there are open-source solvers, such as OR-Tools (Google OR-Tools, 2023).

3.2.3 UGV and tractor path planning

The risk map generated is also required to compute both UGV and tractor path planning. Nevertheless, neither the UGV nor the tractor presents the advantage of being able to change the canopy side in the middle of the row. Hence, it is assumed that both follow simple path planning patterns, such as the boustrophedon (Choset and Pignon, 1998; Mier et al., 2023), meaning that the platform/machine follows a simple back-and-forth in each vineyard row.

3.2.4 Experiments

The experiments took place during the 2021 and 2023 campaigns, to collect a dataset from a commercial vineyard *Vitis vinifera* cv. Loureiro of 1.06 hectares infested with *Botrytis cinerea*. In order to acquire the biophysical parameters of the vineyard, a DJI Matrice 300 (DJI Sciences and Technologies Ltd., Shenzhen, Guangdong, China) embedded with a Micasense ALTUM-PT (AgEagle Sensor Systems Inc., Wichita, KA, USA) was flown over the vineyard. Using this information, the operation of a UAV with a spray tank was simulated, considering the DJI Agras T40 specifications, with a battery life of 12 minutes.

3.3 Results

3.3.1 Heatmap to spraying routes: simulation

For the purpose of this research, simulation heatmaps with three levels of increasing density of spraying areas (low, medium, and high) were generated to compare the path length and spraying time that a UAV, a UGV and a tractor would require to apply the chemical to the hotspots observed in the heatmap. The low-density area considers that less than 25% of the field should be inspected, whereas the medium and high areas include a threshold below 50% and below 75%, respectively. In the case of the simulation scenarios, the low-risk presents a 21.1% of affection, and the medium and high-risk areas a 43.8% and 66.6%, respectively. Figure 3.4 displays the path(s) that should be followed by the UAVs to spray the risk areas, in increasing order of density. A risk area is considered a canopy side of a plant with the likelihood of developing the disease. The number of robots can be interpreted as either the number of platforms flying synchronously over the field or the number of sessions required for a single UAV to spray the area. For instance, in the case of low density (Figure 3.4a), the field can be sprayed in one session using 3 robots or in three sessions, using a single UAV each time. This value is selected considering a maximum battery life of 12 minutes per UAV.

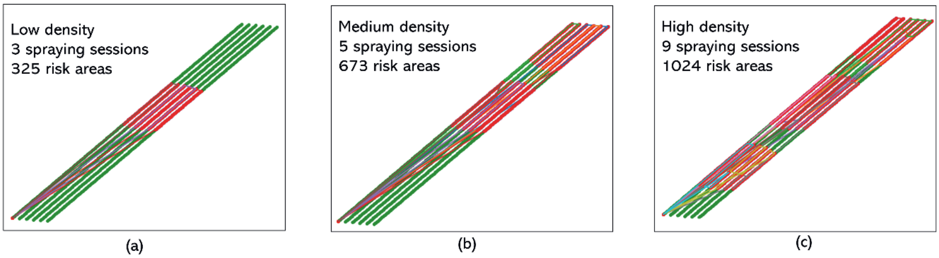


Figure 3.4. Optimal routes for precise spraying in areas with Botrytis Bunch Rot risk based on simulated heatmaps, along with the number of robots or days required to spray the whole field, and the number of risk areas identified. Each line represents the route to be followed by each UAV or day. Further, the green dots are the locations that do not require UAV spraying and, the red ones are the sprayed locations. (a) Low-density areas. (b) Medium-density area, with two localised hotspots. (c) High-density of BBR risk.

To compare the travelled distance and the spraying time between a UAV, a UGV, and a tractor, several factors are taken into account. It is assumed that 5 seconds are needed to spray each risk area for UAVs since they need to stop flying to apply the chemical. For UGVs, it is considered that the speed is lowered by half when spraying since they can spray while continuing to the next location, without the need to stop. Finally, tractors spray at a constant speed without stopping at each plant since they generate a phytosanitary cloud that reaches the whole plant. The speed of a UAV is assumed to be 4 m/s (Qin et al., 2016; Xue et al., 2016) and is considered to be 1.1 m/s (4 km/h) for the UGV (HSE-URV, 2023) and the tractor, as recommended by the provider. In the case of the UGV and tractor, they require some extra space at the end of each row to be able to turn and change the canopy side or row. This value is assumed to be 2 meters to leave the row, two to turn, and two to come back to the original point (6 meters in total). It is assumed that it takes 60 seconds at the end of each row to change sides or rows. Further, neither the UGV nor the tractor can change rows in the middle of the vineyard, as a UAV can do by flying over the canopy. Hence, in both cases, it is considered that the total length of the row should be followed, which corresponds to approximately 110 meters long each. A total of six rows were inspected, and both canopy sides should be considered. Hence, the travelled distance consists of 6 x 2 x 110 meters, plus the turning space.

It can be observed in Figure 3.5 that for the low-density area UAVs present a shorter spraying time compared to tractors and the difference is larger with UGVs, whereas this distance is reduced in all cases with increasing levels of density, being UAVs the least recommendable options for high-risk areas. In the case of the travelled distance, there is a big difference between UAV and UGV/tractor for a low density of risk areas. Nevertheless, since both UGV and tractor travel the same distance regardless of the risk level, almost the same distance is travelled for a UAV, UGV and tractor for a medium density level. Lastly, in the case of a high-risk level, the distance travelled is larger for UAVs than any other platform because of the continuous cycle of UAVs returning to recharge their batteries and the spraying tank.

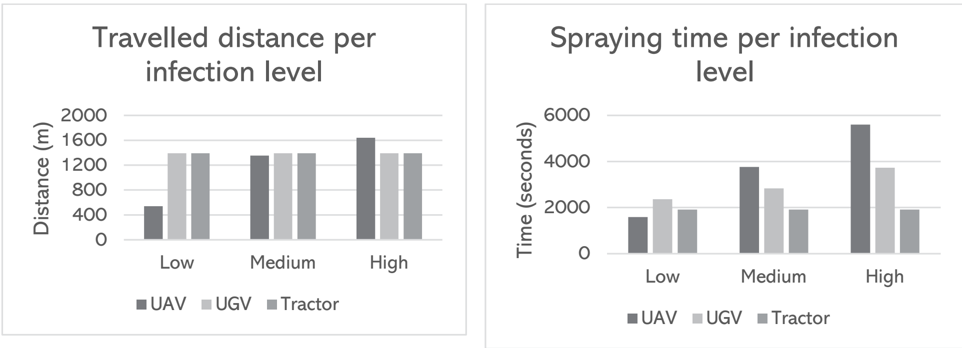


Figure 3.5. Comparison of the travelled distance (meters) and the spraying time (seconds) in a simulation scenario between the UAV, UGV, and a tractor, for the three levels of increased risk density.

3.3.2 Heatmap to spraying routes: real data

In order to validate the calculations of the simulation in a real scenario, two experiments were carried out in a 0.1-ha vineyard during the 2021 and 2023 campaigns. For 2021, there was a total of 38.1% risk areas and 21.6% for the 2023 campaign. Therefore, they were classified into medium and low-density areas, respectively. Figure 3.6 displays the BBR heatmap of each campaign, along with the UAV spraying routes.

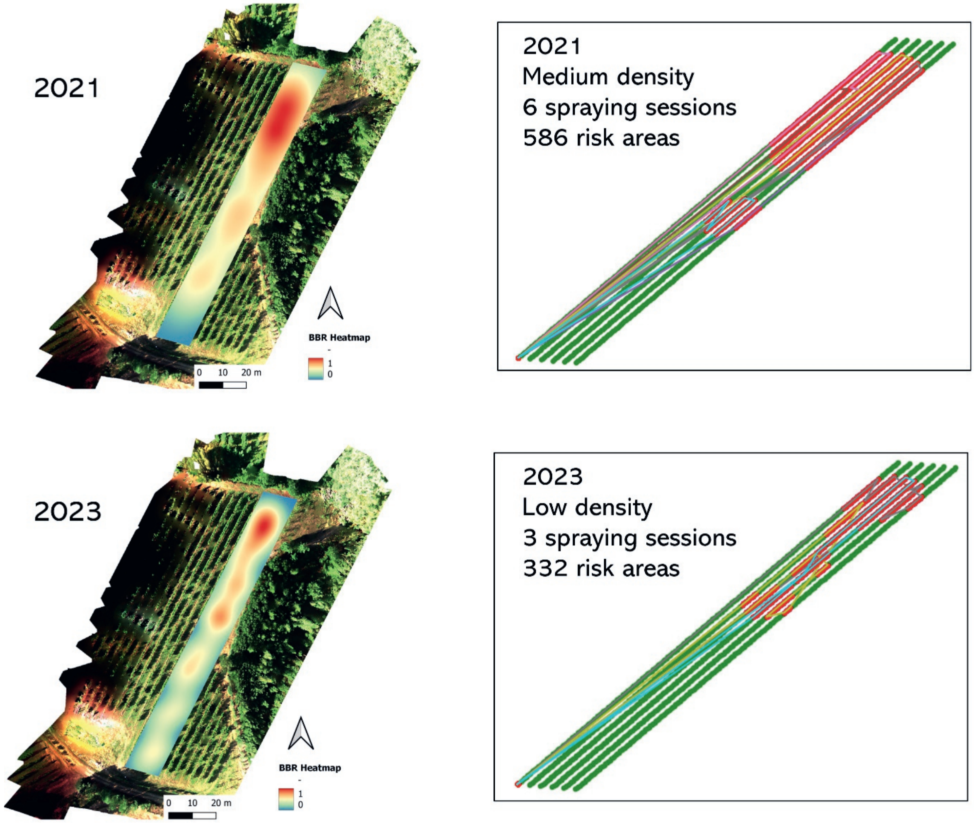
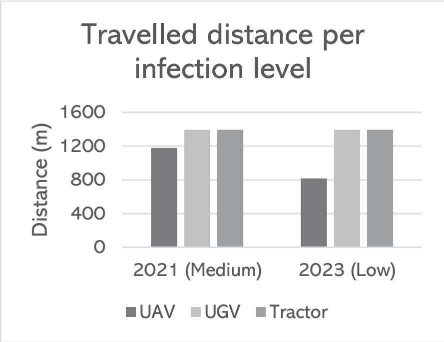


Figure 3.6. Botrytis Bunch Rot heatmap (left) and optimal spraying routes depending on the infection risk level (right), for both 2021 and 2023 campaigns.

Similarly to Figure 3.5, Figure 3.7 provides a comparison of the spraying time and travelled distance that a UAV, a UGV, and a tractor would require to spray the vineyard against BBR. The same travelling speed and additional distance at the end of the row, as explained in Section 3.1, apply to the real data. The real scenario comparison shares the same trend as the simulation. For the low-density areas, UAVs require less spraying time and travelled distance compared to UGVs and tractors. Nevertheless, with increasing levels of risk density, UAVs increase the spraying time required compared to the other platforms/machines.



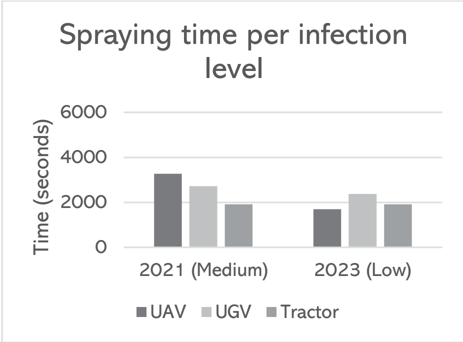


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Figure 3.7. Comparison of the travelled distance (meters) and the spraying time (seconds) in a real scenario between the UAV, UGV, and a tractor, for the two campaigns.

3.3.3 Economic, energy, and sustainability analysis

This subsection includes a comparison of the economic cost of acquiring and carrying out spraying with a UAV, UGV, and a tractor.

3.3.3.1 Purchase and usage cost (electricity/fuel)

As mentioned earlier, the DJI Agras T40 was selected since it has a large tank capacity compared to other UAVs. It has a battery life of 12 minutes (considering the average flight time with full and empty tanks) and its cost is 29.000€ (Ibericadron, 2023). The UGV selected was the XAG R150 because of its large tank capacity. It has a battery life of 4 hours and costs 30.000€ (HSE-URV, 2023). Regarding the purchasing cost of the tractor, according to (Vázquez Torres, 2010), the spraying task represents 15% of the total number of hours that a tractor is used per campaign. Hence, only 15% of the tractor cost is considered for spraying. Assuming an 80.000€ tractor and a sprayer tank of 17.500€, which are common prices for a vineyard tractor and sprayer (Tractores y Máquinas, 2023), the cost contemplated is 29.500€.

The manufacturers provide the values of the battery capacity of the UAV and UGV. Since the UGV carries two batteries, the capacity is multiplied by two. The kWh cost is assumed to be 0.17 €/kWh according to the current price provided by the electrical company (Iberdrola, 2023). The diesel consumption of the tractor is assumed to be 12 L/h. This value has been obtained empirically. The cost of agricultural diesel is 1.2 €/L as given by the diesel company (Repsol, 2023). Table 3.1 summarises the costs of acquiring each option, along with the electric/diesel cost per hour. The last column (cost in €/h) is calculated by considering the capacity or fuel consumption, the hourly cost, and the battery life of each platform. For example, the UAV has a capacity of 1.5666 kWh with an hourly cost of 0.17 €/kWh, resulting in a cost of 0.26 € per battery cycle. Since the battery lasts for 12 minutes, the cost of using the UAV for 60 minutes (1 hour) is 1.33 €.

Table 3.1. Cost of acquiring and utilising the UAV, UGV, and tractor + sprayer per hour.

Machine/robot	Purchase cost (€)	Capacity (Wh)	Battery life (min)	Cost (€/kWh)	L/h	Cost (€/L)	Cost (€/h)
DJI Agras T40	29,000	1566.6	12	0.17	NA	NA	1.33
XAG R150 UGV	30,000	1924	240	0.17	NA	NA	0.08
Tractor + sprayer	29,500	NA	NA	NA	12	1.2	14.40

3.3.3.2 Treatment cost

Traditional methods apply the chemical to all plants, without discriminating the infested and non-infested vines. The difference between applying to all plants and only to plants with the potential of being infested leads to a reduction of up to 78% of chemical products since, according to Figure 3.7, only 21.6% would be sprayed in 2023 and 38.1% in 2021. Hence, the lower the number of risk plants, the higher the difference between considering a precise application compared to traditional methods. Nevertheless, there are alternatives for tractors to apply the chemical only to infested plants with variable rate application (Papadopoulos et al., 2024), for instance, by opening and closing the nozzles with the assistance of a prescription map (heatmap). The purchasing cost of the tractor and the diesel cost remains the same, applying with or without precision, but there is a high difference in the phytosanitary cost. In this study, all platforms/machines are considered to execute precise applications.

By implementing a precise application using the heatmap provided by the early disease assessment UAV flight, the volume of chemicals used is lower and hence, the phytosanitary cost is also reduced. Consider, for instance, the biological fungicide Serenade ASO (*Bacillus subtilis*) (Bayer, 2023), which is commonly used to treat BBR disease. The recommended dose is 4 litres/ha of phytosanitary diluted in 1000 litres of water per hectare. This is the dose that a tractor with a non-variable rate application applies. However, assuming that the UAVs and UGVs apply only to the plants with potential of being infested, this amount is reduced to 0.864 litres/ha (21.6% of 4) during the 2023 campaign and 1.524 litres/ha (38.1% of 4) in 2021. Considering a purchase price of 20€/litre (Nexles EU, 2023), instead of costing 80€/ha, the cost would be 17.28€/ha in 2023 and 30.48€/ha for 2021. Hence, it is recommended that a precise application be carried out in order to lower the volume of phytosanitary used and obtain a more sustainable product, which can also translate to higher revenue for the farmer. Nevertheless, it is important to remark that the tank size of the both UAV and UGV is smaller than the tractor (40 litres and 150 litres, respectively, instead of 2,000 litres) and hence the concentration applied is the same but the amount of chemical applied is lower. However, in this study, tank capacities and phytosanitary volume have not been considered a restriction and hence, the comparison is executed similarly for UAVs and UGVs.

3.3.3.3 Hours to hectares: conversion

The conversion between cost per hour and per hectare is done by considering the required time to spray the 0.1 ha field and assuming that the time needed and the surface sprayed follow a linear correlation. From Figure 3.5 and Figure 3.7 it can be extracted that the time needed to spray 0.1 hectares of a medium-risk area (2021) is 3272 seconds for the UAV, 2720 for the UGV, and 1920 for the tractor. Further, the time required to spray a 0.1-hectare field with simulation medium risk is 3766 seconds for UAV, 2838 for UGV, and 1920 for tractor. Therefore, considering the five scenarios provided (3 simulations and 2 real, sorted by % of disease affection) the correlation between time and surface sprayed is the one displayed in Table 3.2 converting the seconds to hours:

Table 3.2. Hours per hectare conversion for precise spraying for the five scenarios: 3 simulated (low, medium, high) and 2 real (low, medium).

	Simulation low (21.1%)	**Real low (21.6%)**	**Real medium (38.1%)**	**Simulation medium (43.8%)**	**Simulation high (66.6%)**
UAV	4.4	4.7	9.1	10.5	15.6
UGV	6.6	6.6	7.6	7.9	10.5
Tractor	5.3	5.3	5.3	5.3	5.3

This conversion value per infection risk and platform is used to transform the cost of using each robot/machine per hour to the utilisation cost per hectare and to translate the phytosanitary cost per hectare to the cost per hour. This conversion showcases the time efficiency of tractors for pesticide spraying except for the low scenarios, where UAVs present an advantage, and highlights a difference of 3-5 hours per hectare between UAVs and UGVs for low and medium-risk scenarios.

3.3.3.4 Total spraying cost

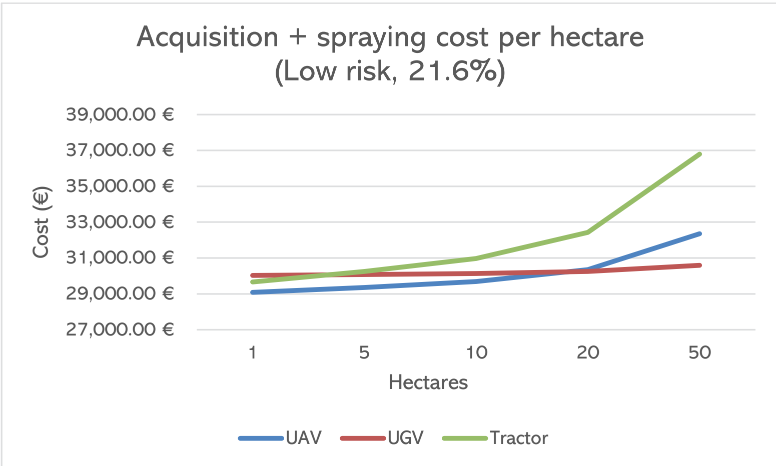
The cost of acquiring and using each machine/robot can be expressed per hour of usage or per hectare (Equation 12):

$$C_i = P_i + (V_i + P_i \cdot M_{rate} + Tr + O) \cdot J \tag{12}$$

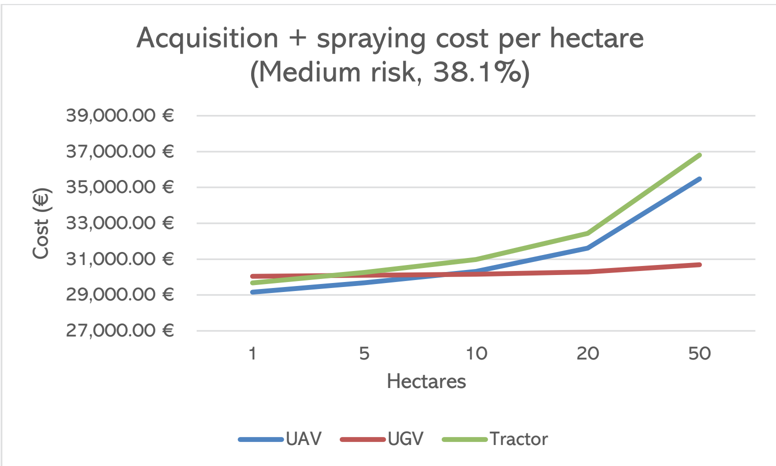
Where C_i is the cost of purchasing and utilising the machine i, P_i is the fixed purchase cost, V_i is the variable cost per hour of use, O is the cost of having a field operator, M_{rate} is the maintenance cost rate, expressed as a decimal, Tr is the treatment cost, J is the number of hours or hectares the machine is used. This research assumes that phytosanitary tank capacity is not a limiting factor, and maintenance costs accrue in proportion to both the initial cost of the machine and its usage over time at a 0.025 annual rate and considering 450 as the average annual hours of use (Molenhuis, 2020). The same M_{rate} value is applied to the UAV and UGV for simplicity.

Regarding the field operator cost, it is considered that both a tractor and a UAV require an employee to drive the tractor or to assist/supervise the spraying task of the UAV, according to EU regulations. Nevertheless, this is not the case for UGVs. Considering the minimum interprofessional brutto salary of 1,748.34€ a month (Gobierno de España, 2024) and the conversion of hours to hectares, this cost is added to the spraying cost of both UAVs and tractors.

Figure 3.8 displays the cost of purchasing and spraying with the three machines/robots per hectare with a low, medium, and high risk of developing the disease. The first two scenarios are computed with the real data and the high scenario is calculated with the simulated scenario, to provide an overview of the difference in platform cost for the three different percentages of disease infection. It can be interpreted that, where the lines cross each other, the cost of acquiring and spraying per hectare is the same for the two platforms/machines. For instance, for a low-risk scenario, the UAV is the cheapest option to spray 1 ha, but after 19ha lifespan, the UGV becomes more competitive. The same trend is repeated for the other two scenarios, but the UGV becomes cheaper than the UAV at 9 and 5 ha, respectively, which is reasonable since UAVs are a better option when there is a localised outbreak but not for high levels of infection when the conversion hours to hectare is higher and UGV highlight their advantage of not requiring a field operator. Lastly, tractors become more competitive than UGVs until 4.5 hectares for both low and medium-risk areas. Moreover, tractors are a more recommendable option than UAVs after 6.5 ha for high-risk areas.



(a)



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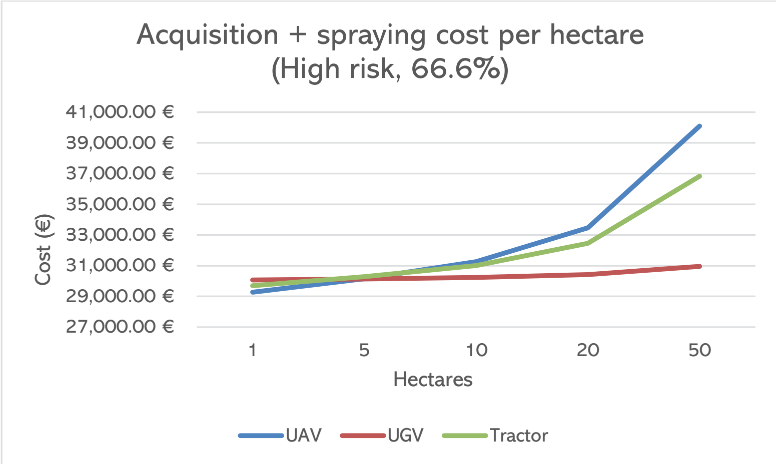


(c)

Figure 3.8. Acquisition and spraying cost per hectare of the three machines/robots considered: UAV, UGV, and tractor (a) for a real low-risk scenario, (b) real with medium risk, and (c) simulated with high risk.

3.4 Discussion

This study presents a methodology that offers significant environmental benefits in vineyard management. By utilising UAVs equipped with multispectral cameras for disease assessment and chemical tanks for spraying, the approach provides an accurate mapping of the biophysical characteristics of the vineyard with its consequent accurate chemical application by taking into account the exact stage of development of the crop. Furthermore, dividing the spraying into two phases: (1) general overview flight to map the disease risk, and (2) closer flight for actual spraying, there is a better usage of the battery lives, which was one of the drawbacks of spraying as analysed by (Hafeez et al., 2023).

Both UAV and UGV path planning for accurate spraying have been researched (Chakraborty et al., 2022; J. Li et al., 2023; Nanavati et al., 2023; Xu et al., 2023). Nevertheless, the biophysical parameters of the field and battery constraints were not considered. Furthermore, the fact that UAVs can fly over the canopy and change side/row provides a great advantage over UGVs when executing path planning in vertical trellis systems. Therefore, this study has focused on vineyards and did not consider a continuous crop, such as wheat or maise. This method does not cover the whole field as done by spraying algorithms that consider CPP (Becce et al., 2021; Guo et al., 2021; Li et al., 2023; Pham et al., 2020). Therefore, it minimises the overall use of agropesticides up to 78%, similar to (Vélez et al., 2023c), since the phytosanitary are applied only to the vines that have a higher risk of developing the disease, which represented 21.6% in the case of the 2023 campaign, and 38.1% in 2021. Lowering the overall use of phytosanitary by carrying out a precise application is key to improving the sustainability of the vineyard while reducing the input cost. Detecting the disease is not sufficient, it should always be accompanied by a precise and efficient chemical application. In addition, the proposed method considers an important challenge in real vineyards, which is fruit occlusion. Therefore, the method is designed to spray the grape bunch through several points of view to avoid the phytosanitary not reaching the actual target, with its consequent chemical waste. Hence, it is a step toward mitigating the environmental impact associated with intensive phytosanitary use (Etienne et al., 2022; Patinha et al., 2018).

Figure 3.5 and Figure 3.7 indicate that when there is a focus on infection (lower than 25% of plants with a risk of developing the disease) UAVs travel by up to 41% less distance than UGVs tractors. Further, UAVs require up to 32% less spraying time compared to ground robots and up to 17% less than tractors, similar to (Becce et al., 2021), which can also be understood as a lower energy/fuel consumption and battery usage, analogous to the results obtained by (J. Li et al., 2023). Nevertheless, when there is not a focus on infection but there is widespread risk of developing BBR, UAVs require 291% more spraying time than a tractor and 150% more than a UGV. Moreover, they travel 117% more distance than tractors and ground robots due to battery limitations. Hence, UAVs become competitive when there is a low percentage of risk plants. In that line, an optimal approach to utilise UAVs would be to assess the presence of BBR disease at the early stages of development to avoid it being spread through the vineyard. In that sense, the disease would be efficiently treated through precise low-volume applications and the distance travelled and spraying time would be reduced.

The economic analysis of this study has allowed the understanding of the price evolution of machine/robot purchases along with their usage and the potential risk of disease. Figure 3.8 shows that for UAV pesticide treatment to be worthwhile, it is essential to treat in the early stages of infection when disease symptoms are localised in specific foci and the percentage of surface involvement is low. To this end, UAV monitoring can be especially useful. Further, UAVs present a great advantage over UGVs and tractors at a low number of hectares for the three levels of infection, whereas the difference is reduced with an increasing number of sprayed hectares. The advantage of UGVs of not requiring a field operator is highlighted for high-risk areas since their cost is greatly reduced due to hours to hectares conversion and UGVs become more competitive to any other platform after 5 hectares. Nevertheless, this benefit is likely to diminish over time due to evolving regulations and advancements in UAV technology, such as the recently introduced DJI Dock. As field operators are not required and UAV operations become more cost-effective, this UGV advantage will gradually recede.

UAVs present another sustainable advantage over UGVs and tractors in the context of Controlled Traffic Farming (CTF) (Gasso et al., 2013; Vermeulen et al., 2010). UAVs operate entirely above the soil surface, eliminating the risk of soil compaction (Batey, 2009; Nawaz et al., 2013). Soil compaction can negatively impact crop growth, root development, and overall soil health, leading to decreased yields and increased environmental degradation (Lagnelöv et al., 2020). Additionally, in CTF systems where designated traffic lanes are utilised to minimise soil compaction, UAVs offer even greater benefits by bypassing the need for physical ground contact. By leveraging UAV technology in agricultural spraying operations within CTF frameworks, farmers can optimise crop health and productivity while simultaneously reducing environmental impact and preserving soil structure for sustainable farming practices.

The ability to interpret the number of UAV routes as either the number of platforms flying synchronously or the number of spraying sessions for the field provides flexibility. This flexibility allows for optimal timing in phytosanitary application, ensuring that treatments are applied only to diseased plants, contributing to sustainable vineyard management (Perria et al., 2022). Furthermore, spraying with multiple UAVs synchronously shows the advantages of applying the chemical in a short period of time, for instance, after rain. The sooner it is sprayed, the less likely it is that the disease will develop. In future versions of the algorithm, computer vision methods could be integrated for detecting cluster phenology (Ariza-Sentís et al., 2023b; Santos et al., 2020; Torres-Sánchez et al., 2021).

3.4.1 Limitations and future work

In the case of diseases that affect the canopy and hence the symptoms are visible, route optimisation can be combined with object detection for actual disease detection. In this regard, farmers would benefit from a whole disease assessment framework, starting with an aerial inspection to produce the heatmap, and a subsequent UAV path planning to spray the areas with a higher likelihood of developing the disease following the optimised spraying route. Furthermore, further efforts should consider the cost of spraying against other diseases that affect the canopy and not only the fruit since in those cases, there is a lower precision of phytosanitary application since the product is applied to the whole canopy.

The application of phytosanitary is different when applied with a UAV or UGV than with a sprayer in a tractor since they don't have the same tank capacity and hence the volume applied is lower even if the concentration remains the same. Therefore, it is important to research the appropriate concentrations in low-capacity sprayers to avoid leaf damage. Nevertheless, in this study tank capacity was not included as a constraint for the robot to come back to fill the tank since battery limitations were considered to be more restrictive and hence, when the robot returns home to charge the batteries, the tank is filled.

Finally, due to the scope of the current research, this study mainly examines how UAVs and UGVs are used for precision agriculture in vineyards, but it does not totally explore their broader economic and technological impacts on businesses and farmers (Lowenberg-DeBoer et al., 2020; Wachenheim et al., 2021). This limitation underscores the necessity for a more complete investigation into the long-term viability of these technologies within the agricultural sector. Understanding the value of investing in UAVs and UGVs for agriculture involves examining their depreciation rates, lifespan, real maintenance cost, and operational costs (Mohsan et al., 2022; Yowtak et al., 2020) alongside the potential for governmental incentives (Omotilewa et al., 2019; Y. Shen et al., 2023). Additionally, reducing chemical use aligns with sustainability goals, potentially leading to long-term savings and public health improvements (Cooper and Dobson, 2007). These factors are crucial in assessing the investmentworthiness of these technologies. Also, considering market trends and the benefits of economies of scale of UAVs and UGVs in vineyard management could make adopting these technologies more economically viable, as happened to other agricultural technologies (Finco et al., 2023). Therefore, more in-depth research is suggested to fully understand the social and economic effects and the challenges of using such technology in agriculture for the successful use and acceptance of UAV and UGV technologies in farming.

Future research could consider UAV-UGV integration (Vu et al., 2018). In that scenario and in order to calculate the optimal distance to the plant for accurate spraying, considering the weather at the exact moment of application, Computational Fluid Dynamics (CFD) (Chung, 2002; Giahi et al., 2023) can be taken into account in the future.

3.5 Conclusions

The methodology proposed in this study represents a significant advancement towards sustainable vineyard management, by reinforcing UAV technology for precise disease assessment and pesticide application. By utilising raw multispectral imagery and biophysical parameters, the approach enables the generation of accurate disease risk maps, facilitating targeted spraying only on infested plants. This targeted approach results in a substantial reduction in pesticide usage, with up to a 78% decrease compared to traditional methods. Moreover, the method addresses challenges such as fruit occlusion by employing multiple perspectives for spraying, thus minimising chemical waste and environmental impact. The two-phase framework of mapping disease risk before actual spraying optimises battery life and ensures efficient utilisation of resources, marking a significant step towards mitigating the environmental consequences of intensive phytosanitary use in vineyards. For UAV pesticide treatment to be effective, it is crucial to execute it during the initial stages of infection, when disease symptoms are concentrated in specific areas where up to 25% of the plants present a risk of developing the disease and the extent of surface damage is minimal since they lower the travelled distance and spraying time up to 41% and 49%, respectively, compared to tractors and UGVs. Furthermore, the economic analysis revealed that UAVs are recommended for all risk scenarios until 19 hectares, when UGVs become more competitive for low-risk, and 9 and 5 hectares for medium and high-risk, respectively. Further, tractors are more competitive than UAVs after 6.5 hectares for high-risk areas. Nevertheless, the methodology's flexibility can allow for synchronising multiple UAVs or spreading spraying over several sessions, enhancing the adaptability and efficacy of vineyard management strategies and contributing to long-term sustainability. Future research should focus on optimising spraying concentrations for UAVs and UGVs, further improving efficiency and reducing chemical usage.

Data access

All data collected for this chapter were carefully post-processed and uploaded open access to Zenodo. A detailed scientific manuscript was published. This allows other researchers to reproduce the experiment and conduct their own experiments using the collected data.

Vélez, S., Ariza-Sentís, M., Valente, J., 2023. Dataset on unmanned aerial vehicle multispectral images acquired over a vineyard affected by Botrytis cinerea in northern Spain. Data Brief 46, 108876. https://doi.org/10.1016/j.dib.2022.108876

Chapter 4

UAV-based grape bunch detection for precision farming. Use case: phenotyping

This chapter is based on:

Ariza-Sentís, M., Baja, H., Vélez, S., & Valente, J., 2023. Object detection and tracking on UAV RGB videos for early extraction of grape phenotypic traits. Computers and Electronics in Agriculture, 211, 108051. https://doi.org/10.1016/j.compag.2023.108051

Abstract

Grapevine phenotyping is the process of determining the physical properties (e.g., size, shape, and number) of grape bunches and berries. Grapevine phenotyping information provides valuable characteristics to monitor the sanitary status of the vine. Knowing the number and dimensions of bunches and berries at an early stage of development provides relevant information to the winegrowers about the yield to be harvested. However, the process of counting and measuring is usually done manually, which is laborious and time-consuming. Previous studies have attempted to implement bunch detection on red clusters in vineyards with leaf removal and surveys have been done using ground vehicles and handled cameras. However, UAVs mounted with RGB cameras, along with computer vision techniques offer a cheap, robust, and timesaving alternative. Therefore, MOTS is utilised in this study to determine the traits of individual white grape bunches and berries from RGB videos obtained from a UAV acquired over a commercial vineyard with a high density of leaves. To achieve this goal two datasets with labelled images and phenotyping measurements were created and made available in a public repository. PointTrack algorithm was used for detecting and tracking the grape clusters, and two instance segmentation algorithms - YOLACT and Spatial Embeddings - have been compared to find the most suitable approach to detect berries. It was found that the detection performs adequately for cluster detection with a MODSA of 93.85. For tracking, the results were not sufficient when trained with 679 frames. This study provides an automated pipeline for the extraction of several grape phenotyping traits described by the International Organisation of Vine and Wine (OIV) descriptors. The selected OIV descriptors are the bunch length, width, and shape (codes 202, 203, and 208, respectively) and the berry length, width, and shape (codes 220, 221, and 223, respectively). Lastly, the comparison regarding the number of detected berries per bunch indicated that Spatial Embeddings assessed berry counting more accurately (79.5%) than YOLACT (44.6%).

4.1 Introduction

Viticulture is relevant in many countries in Europe because of its large contribution to the European socioeconomic sector (Fraga et al., 2012). Of the 7.3 million hectares devoted to vineyards worldwide, 45% of that, 3.3 million hectares, are located in Europe (International Organisation of Vine and Wine, 2021). In the last years, with the growing importance of precision agriculture and specifically precision viticulture, worldwide winegrowers are applying the newest advances in technology to their vineyards to increase accuracy in crop monitoring, precise fertilisation and pesticide application, and yield forecasting, among other activities (Matese and Di Gennaro, 2015).

To this extent, phenotyping is an important tool in agriculture, usually made through field inspections, which are time-consuming and laborious (Rahaman et al., 2015). However, advances in remote sensing, such as the usage of UAVs with multiple types of sensors onboard offer a time-saving alternative to traditional phenotyping. In this sense, computer vision techniques, such as object detection and tracking, come into play as analysis tools for the datasets acquired with the UAVs or UGVs.

Recent studies have focused on phenotyping, mostly on 3D point clouds. Rose et al. (2016) used a vehicle that had multiple cameras mounted on it, capturing 3D data by reconstructing the stereo images of the grapes using point clouds in a vineyard setting to then obtain semantic data of the berry phenotype. Milella et al. (2019) used a similar method to obtain the data using an RGB-Depth camera, which reached an accuracy of 91% of semantically segmenting grapes using the VGG19 neural network architecture (Simonyan and Zisserman, 2014). Rist et al. (2019) utilised predictive modelling and 3D field phenotyping with 360° lab scans of grape bunches as Ground Truth (GT).

Many studies have applied object detection in the field of woody crops, using one-stage or two-stage detection algorithms. For mangoes, Stein et al. (2016) deployed a Faster R-CNN detection algorithm, and Wang et al. (2019) deployed a YOLO-based detection algorithm. A study by Bargoti & Underwood (2017) looked into apples, mangoes, and almonds using Faster R-CNN. Apolo-Apolo et al. (2020) focused on orange detection using image captures from a UAV implementing Faster R-CNN. Fruit identification on canopies is difficult; occluded fruit-on-fruit and fruit-on-leaves are scenarios that simple bounding boxes may not be able to handle. Consequently, extra information is required for precise classification. Adding masks on top of the bounding boxes can significantly increase accuracy as demonstrated by Santos et al. (2020) in a study about grapes. It was found that using Mask R-CNN achieved an F1 score of 0.84 compared to 0.65 for YOLOv2 (considering an IoU of 0.5). In addition, Tian et al. (2019) found that while detecting apples, simple bounding boxes cannot precisely retrieve shape and contour information, which are important additional features for the recognition of fruits. In accordance, Jia et al. (2020) have also achieved similar results to Santos et al. while using Mask R-CNN for apple detection. A recent study from Li et al. (2023) focused on multitask-aware network for fruit bunch detection and region segmentation, obtaining promising results for assisting cherry tomato harvesting in greenhouses.

Several studies in the agricultural field about the detection and tracking of fruits have utilised the Hungarian algorithm or Kalman filter (Kalman, 1960) to track different fruits, such as seedlings, mangoes, apples, and oranges (Jiang et al., 2019; Liu et al., 2018; Z. Wang et al., 2019) with positive results. However, the methods they use are not end-to-end trainable, since they add an additional tracking branch to the detection algorithm (Voigtlaender et al., 2019) (Yang et al., 2019). A standardised detection and tracking framework with an end-to-end trainable algorithm is needed in order to evaluate performance for different objects and research fields.

MOT (Leal-Taixé et al., 2015) is a popular computer vision task that has several existing state-of-of-the-art algorithms. However, the MOT framework is an object detection task, so it uses simple bounding boxes to track objects. MOTS paved the way to much more accessible computer vision research pertaining to object tracking with instance segmentation. Voigtlaender et al. (2019) developed this computer vision task alongside the first novel end-to-end trainable MOTS detection and tracking framework, called TrackR-CNN.

There are several state-of-the-art MOTS algorithms that have been developed such as ViP-DeepLab (Qiao et al., 2020), ReMOTS (F. Yang et al., 2021), and PointTrack (Xu et al., 2020). These algorithms have been tested on KITTI MOTS, a dataset of cars and pedestrians that has been annotated with the MOTS standard. ViP-DeepLab utilises 3D point clouds (Nguyen and Le, 2013) to predict spatial location, temporal class, and a consistent temporal location for each 3D cloud. This temporal consistency helps increase tracking performance for the algorithm. ReMOTS uses a simple self-supervising refining of tracklets from predicted masks. PointTrack learns instance embeddings by converting images into 2D point cloud representations (Neven et al., 2019). These 2D point clouds allow a tracking-by-points system that achieves quite accurate results.

There have been previous studies on MOTS for woody crops. De Jong et al. (2022) implemented additional tracking branches on TrackR-CNN. The additional tracking branches are the Kalman filter and optical flow (Horn and Schunck, 1981). Moreover, PointTrack (Xu et al., 2020) was also implemented showing promising results and potential in apple yield estimation. Nevertheless, they also revealed many challenges in using MOTS for fruit counting and tracking, such as the homogeneity of fruits, the size of the fruits, and the challenging orchard environment. Ariza-Sentís et al. (2022) showed the potential of PointTrack algorithm for grape bunch detection and tracking using UAV RGB videos. Nevertheless, they also faced the same problems of fruit homogeneity and complex environment illumination.

A common technique used in the studies mentioned is the usage of 3D input data of grape bunches for accuracy. Santos et al. (2020) did a study about instance segmentation with grape clusters. The dataset used is a very well-made grape bunch annotated dataset called the Embrapa Wine Grape Instance Segmentation Dataset (WGISD), composed of 300 images showing around 4000 grape clusters. The WGISD is a dataset composed of images from vineyards with a trellis system-based wine grape production, taken with two cameras. Hence, the images taken were very clear and close, with a 1-meter distance from the grapes. The clear and clean images of the grapes bring questions as to whether a model trained with this dataset will be robust enough for images acquired from different platforms, e.g., UAVs. So far, there is a lack of datasets that were taken from UAVs. It is therefore interesting to test images acquired from UAVs, considering the many “all-in-one” uses they have (Tsouros et al., 2019), and their increasing research and use in agriculture (Rejeb et al., 2022).

With respect to the berry counts, Nuske et al. (2011) explored the computer vision field with the Radial Symmetry Transform (Loy and Zelinsky, 2003), which employed the transform to find berry candidates in images. This is further filtered with a ML technique (K nearest neighbour classifier), which then finally performed linear regression on the detected berries. In a further study, Nuske et al. (2014) relayed the difficulty of berry cluster association due to touching clusters from adjacent grape bunches. Hence, a DL method that first detects bunches and subsequently detects berries from that bunch could potentially solve this problem.

The main aims of this article are the following: 1) to detect and track green grape bunches and berries over UAV RGB videos recorded on a commercial vineyard, presenting challenging lighting conditions and leaf occlusion, and 2) to provide phenotypic traits such as the bunch and berry length, width, and shape at a relatively early stage of bunch development, which is critical in viticulture.

4.2 Materials and Methods

The workflow followed in this research is summarised in Figure 4.1. The procedure started by acquiring the UAV RGB videos, with the posterior data cleaning and annotation with the grape bunch and berry labels. Afterwards, the workflow is subdivided into two main branches, the first, in red, is devoted to detecting and tracking bunches, for which the PointTrack algorithm was trained. The second main branch, in blue, aimed at detecting the berries within the already identified grape clusters. Finally, the outputs of the research are the automatically-extracted OIV descriptors for bunches and berries. Further details of each step are provided in the following subsections.

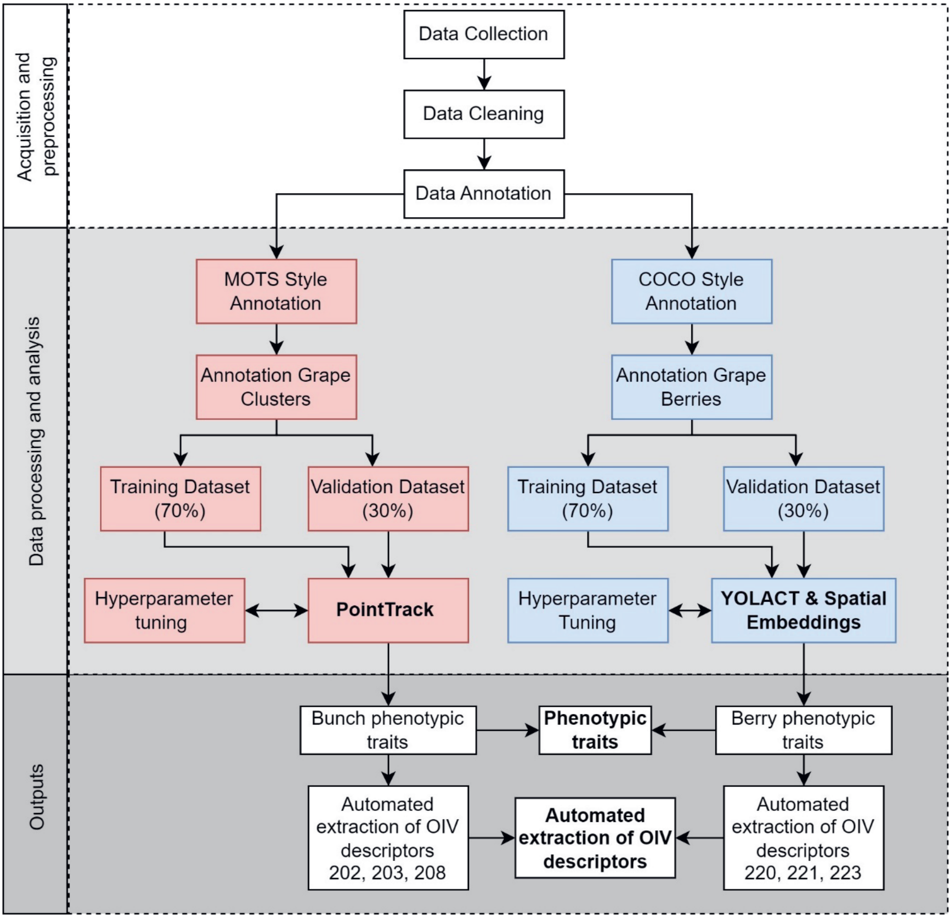


Figure 4.1. Workflow diagram of this study. The common branch for all procedures, in white, consists of acquiring the dataset with the UAVs and the posterior cleaning and annotation of the bunches and berries. In red, is the grape cluster detection and tracking procedure. In blue, the detection of berries. Finally, in white again since it is a common branch, the outputs of the study, are the bunch and berry phenotypic traits and the extraction of OIV descriptors automatically.

4.2.1 Data acquisition

The flights were carried over four rows of a 1.06 ha and 8.1% slope commercial vineyard *Vitis vinifera* cv. Loureiro. The vineyard, property of "Bodegas Terras Gauda, S.A." is located in Tomiño, Spain (X: 516989.02, Y: 4644806.53; ETRS89 / UTM zone 29N) (Figure 4.2). The vines were planted in 1990 with a NE-SW orientation, and grafted on 196.17C rootstock. Spontaneous vegetation species, such as mint, were present between rows. The plants are trained in vertical shoot positioning and managed in a vertical trellis system. The distance between plants and rows was 2.5 × 3 meters, respectively. The vineyard is part of the "Rías Baixas AOP" (Appellation of Origin) and hence, the vineyard is managed following the protocol and legislation of the AOP. No leaf removal was carried out and therefore, the videos present leaf occlusion. Table 4.1 provides all the specifications of the data acquisition regarding the platforms and sensors used.

Table 4.1. Data acquisition specifications.

How the data were acquired	UAV: DJI Matrice 210 RTK Flight speed: 0.7 m/s Flight altitude: 3 m AGL Sensor: DJI Zenmuse X5S Sensor characteristics: focal aperture range: f1.7 - f.16, shutter speed: 1/8000. Video characteristics: frame width: 4096, frame height: 2160, frame rate: 59.94 frames/second. A total of four flights were executed. Each flight recorded one row of the vineyard, whose length is around 110 m.
Description of data collection	The four flights were executed on June 28th, 2021 over four rows of the vineyards. The flights were carried out on a sunny day with wind velocity lower than 0.5 m/s. The four rows were selected according to the ripening stage of the grape clusters, to have a representative sample of the development status over the four rows.
Data source location	City/Town/Region: Tomiño, Pontevedra, Galicia Country: Spain Latitude and longitude (and GPS coordinates) for collected samples/data: 41°57'18.3"N 8°47'41.9"W

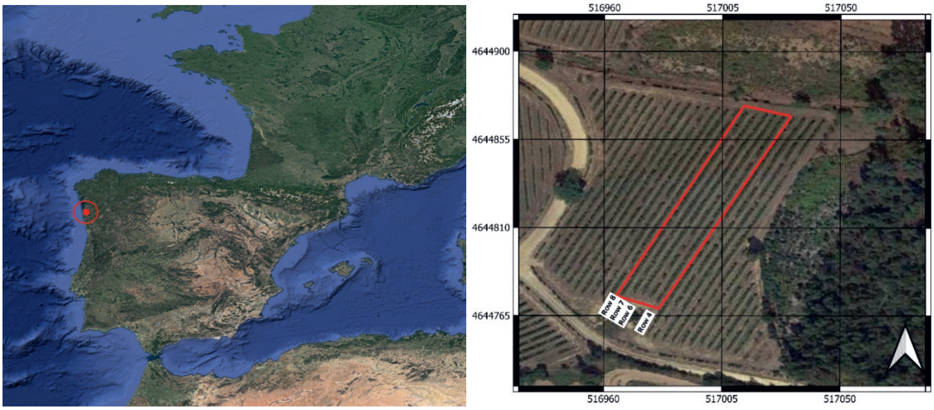


Figure 4.2. Left: Location of the vineyard over the Iberian peninsula (coordinates in WGS84). Right: Location of rows 4, 6, 7, and 8 within the vineyard (coordinates in ETRS89 / UTM zone 29N).

4.2.2 Annotation procedure

During this research two annotation types were used: MOTS to detect and track grape clusters, and COCO to detect berries (Figure 4.3). All the annotations were labelled using CVAT software2 (CVAT.ai Corporation, 2022).

4.2.2.1 Grape bunch dataset

The grape clusters were annotated with a per-pixel accuracy, making sure that only the grapes were annotated, without the peduncle of the bunch. A grape cluster was annotated if it was visible on the camera, even when it was under a shade. In total, 29 video sequences were labelled to detect and track bunches, with a total number of 679 annotated frames. From those videos, an approximate 70/30 split was used for training and testing purposes. For reproducibility and to extend the research done in this field, the dataset and the MOTS labels of the grape clusters were made available (Ariza-Sentís et al., 2023d).

4.2.2.2 Berry dataset

Each visible berry was annotated in each bunch, so occluded berries were ignored in the annotation process. The berries were not annotated across frames because they were not meant to be tracked, only detected. Hence, the dataset was composed of selected frames from the training sequences from the grape cluster dataset. The berry dataset consists of a total of 33 images including 4905 annotated berry masks. From those, an approximate 70/30 split was implemented for training/testing.

Figure 4.3. Example of the annotations produced with the CVAT software. Left: grape bunch dataset used for detection and tracking. Right: berry dataset used for detection.

4.2.3 Algorithms and model evaluation

4.2.3.1 PointTrack for bunch detection and tracking

For the detection and tracking of the clusters, PointTrack was implemented in two steps: (1) training the instance segmentation model (Spatial Embeddings), and (2) training the PointTrack model, for instance, embedding association.

To train the instance segmentation model, an Adam optimiser (Kingma and Ba, 2017) was used with a learning rate of $5\text{x}10^{-5}$, and the finetune training used a learning rate of $5\text{x}10^{-6}$. These learning rates were the best values used in the original implementation of Spatial Embeddings.

To start the pre-training, the image crops of the instance annotations were generated first, so the algorithm could learn from the instance crops. In practice, the authors of PointTrack used the KINS dataset (Qi et al., 2019) that was annotated in the COCO format to produce these instance crops. However, using a custom dataset to generate these instance crops required quite some work to convert them to the right COCO format files.

Other parameters that needed to be defined at the start of the training session were (1) batch size and (2) epochs. A batch size of 20 was used to train the instance crops, considering the high number of available instance crops, and the limitation of memory. A number of at least 50 epochs is needed to let the network learn all the instance crops, in accordance with the number of instance crops available and the batch size. Xu et al. (2020) also used this number when training KITTI MOTS. However, for the grape clusters, this number was not enough to show any meaningful improvement in segmentation performance, therefore, training in increments of 200 was done, then further increased until the performance was stagnating, or overfitting was observed.

Transfer learning (Torrey and Shavlik, 2010) was used to train the Spatial Embeddings model. Hence, pre-trained weights from the KITTI MOTS dataset were implemented to boost the identification of more general features such as shapes, edges, and textures (Neuhold et al., 2017).

Finally, to train PointTrack, Adam optimiser was also used with a learning rate of 2×10^{-3}, in accordance with Xu et al. (2020). The batch size used was 64, considering the memory limitations of the hardware used.

Two metrics were used to evaluate the tracking performance of PointTrack: MOTS (Multiple Object Tracking and Segmentation Accuracy) and sMOTSA (soft MOTSA) (Eq 1, 2).

$$MOTSA = \frac{|TP| - |FP| - |IDS|}{|M|} \tag{1}$$

$$sMOTSA = \frac{\tilde{T}P - |FP| - |IDS|}{|M|} \tag{2}$$

where:

TP are true positives, number of masks mapped to ground truth masks (where IoU>0.5)

$\tilde{T}$P are soft true positives, the sum of the IoU of all true positives.

FP are false positives, the number of masks that are not mapped to a ground truth mask.

IDS are id switches, ground truth mask in which its ID was switched in a previous frame.

M is the number of ground truth masks.

Concerning the detection performance, MOTSP (Multiple Object Tracking and Segmentation Precision) and MODSP (Multiple Object detection and Segmentation Precision) were calculated (Eq. 3, 4).

$$MOTSP = \frac{\tilde{T}P}{|TP|} \tag{3}$$

$$MODSP = \frac{TP}{|TP|} \tag{4}$$

4.2.3.2 YOLACT and Spatial Embeddings for berry detection

The implementation of YOLACT was straightforward since it was declared in the config file that contained various configurations such as backbone network, iterations, batch size, and dataset path, among others.

The COCO detection metrics used mAP (mean average precision) as its ultimate metric, to determine how precise an instance segmentation model could predict the masks compared to a ground truth annotation. The mAP was calculated using precision and recall (Eq. 5, 6, 7).

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$AP = i \sum_{Recall_i} Precision(Recall_i) \tag{7}$$

where: FN is the false negatives, which is the number of segments from the precision-recall curve.

4.2.4 Phenotyping assessment

OIV has many standards for the vineyard ecosystem, which include the classification of grape bunches and berries for several purposes, such as phenotyping. One of these standards is a characteristic that defines phenotyping of bunches and berries and is represented with an OIV code (International Organisation of Vine and Wine, 2009). OIV numbers are useful for winegrowers to determine the intrinsic characteristics of their varieties. The OIV codes can represent quantitative or qualitative characteristics, such as the number of consecutive tendrils or the degree of resistance to a certain disease, respectively.

In this study, several OIV characters were extracted from the identified bunches and berries. For bunches, the length, width, and shape of the bunch are defined as OIV codes 202, 203, and 208, respectively. For berries, the length, width, and shape are defined as OIV codes 220, 221, and 223, respectively. Figure 4.4 visually indicates how OIV codes 202 and 203 are measured in the bunch. The guidelines to measure the rest of the OIV characters can be found in the descriptor list of the OIV (International Organisation of Vine and Wine, 2009).

The OIV establishes that to determine descriptors, 10 bunches, and 30 berries should be considered and therefore, a total of 10 bunches and thirty berries were considered to extract their respective OIV descriptors.

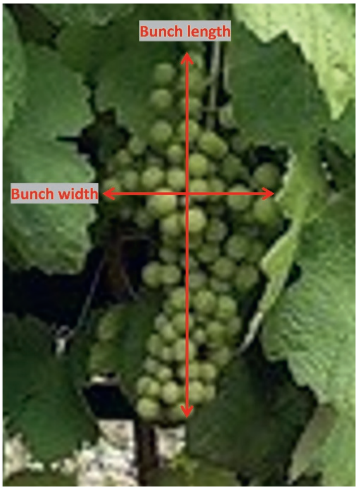


Figure 4.4. OIV codes 202 (bunch length) and 203 (bunch width).

To automatise the extraction of the OIV descriptors, the length, and width of the bunch were obtained using two methods. The first one consisted of cropping the image to the mask size and extracting the length and width of the image properties to convert them to OIV 202 and 203 descriptors. However, this method considered that the bunch was oriented downwards, which was not the case in all bunches and also at an early stage of development since the weight of the bunch was still not sufficient to drive the bunch in a downward position. Hence, a second method was considered. This second method consisted of identifying the largest distance within the mask and rotating the mask so that it had a 0-degree angle to the vertical axis. Afterwards, the width was detected as the second largest distance perpendicular to the previous one identified. To obtain the OIV descriptors of the berries, because of their spherical nature, the first method mentioned for the bunch was implemented. To validate, all metrics were compared to the ones visually assessed and measured in the video frames that were annotated, and mentioned as ground truth data in the rest of the document.

The conversion from pixels to cm was done by information on the pole width of each video sequence. Since the flights were performed in manual mode, each sequence had a slightly different length from the grape clusters, and the ratio of conversion was different for each video sequence. The poles from the vineyard had a fixed width of 9 cm. Hence, a ratio for each sequence was defined in Eq. 8.

$$Ratio\ cm/pixel = \frac{Pole\ width\ (cm)}{Pole\ width\ (pixel)} \tag{8}$$

To assess the bunch shape, the OIV establishes that the focus should be located between the third fourth and fifth of the bunch. To automatise it, the already downward-oriented mask was cropped into five pieces and the third and fourth starting from the top were selected. Afterwards, the ratio between the top and bottom width was used to classify the shape of each bunch (Figure 4.5). If the ratio was below 1.1, it was classified as level 1, bigger than 1.3 was level 2. Lastly, between 1.1 and 1.3 was considered level 3.

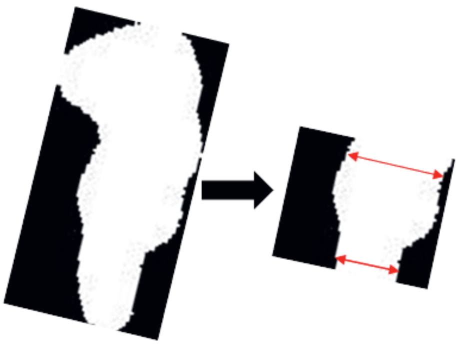


Figure 4.5. Selection of the third and fourth fifth of the grape bunch to obtain OIV 208. The red arrows represent the top and bottom widths to calculate the ratio and classify it within an OIV level.

Regarding the berry shape, a visual inspection was performed first to corroborate that all berries of the Loureiro variety were spherical. Because of that, they could only belong to levels 1 to 4. The ratio between the length and the width was calculated to categorise the berries. If the ratio was below 0.95 it was classified as level 1, between 0.95 and 1.05 level 2, between 1.05 and 1.25 level 3 and finally, larger than 1.25 was considered level 4. These values were selected to quantify the qualitative levels of the OIV regulations.

Finally, a comparison between the number of the berries annotated inside each bunch and the amount of berries identified by both YOLACT and Spatial Embeddings was calculated to assess the feasibility of berry counting for each algorithm.

4.2.5 Hardware

A high-performance computer (HPC) was used to implement the models of PointTrack, YOLACT, and Spatial Embeddings. It was equipped with two Nvidia RTX Titan GPUs with 24GB of GDDR6 memory, running on Linux, Ubuntu 20.04.1 LTS. Furthermore, it was also equipped with 64GB of memory and an Intel© Core™ i9-10940X CPU @ 3.30 GHz × 28 to support the training and testing process of the algorithm.

4.3. Results

4.3.1 Bunch detection and tracking

In total, five models were generated with PointTrack (Table 4.2). In addition to the crop instance, the number of epochs was changed in the PointTrack training. The training schemes are shown, with details on how they were deployed. The last model shown in Table 4.2, "*BoxApp128_200+1200*", was trained with transfer learning from the apple dataset used by de Jong et al. (2022).

Table 4.2. Configuration of the five models generated with PointTrack. "Rec" stands for rectangular-shaped crop instance, "Box" refers to models generating bounding boxes, "SE" stands for Spatial Embeddings and "FT" for finetuning.

No.	Model Name	Time (h)	Epoch	sizes
1	Rec64_600+1200	~ 33	600SE + 1200FT	64 x 128 → 128 x 256
2	Rec128_800+3200	~ 60	800SE + 3200FT	128 x 256 → 256 x 512
3	Box80_800+2400	~ 48	800SE + 2400FT	80 x 80 → 160 x 160
4	Box160_1000+2400	~ 55	1000SE + 2400FT	160 x 160 → 320 x 320
5	BoxApp128_200+1200	~ 26	200SE + 1200FT	128 x 128 → 256 x 256

The results of the bunch tracking with the PointTrack algorithm are shown in Table 4.3. The tracking metrics have a negative value due to false positives and hence, for the goal of phenotyping with the masks, the detection metrics are given more emphasis than tracking metrics. Across the models, the results of detection are quite consistent, with a 66% performance. The model "*Rec128_800+3200*" performed the best in the MODSA metrics, achieving a 10% increase compared to the second best. The second-best model was also the model trained with rectangular-shaped crop instance, "*Rec64_600+1200*". The model trained with transfer learning from APPLE MOTS, "*BoxApp128_200+1200*", was one of the worst-performing models, indicating transfer learning did not improve inference for grape bunch detection. Additionally, "*Rec128_800+3200*" also had the least amount of ID switches, meaning that tracking of that model worked better than the rest.

Table 4.3. Results of grape bunch tracking and detection with PointTrack. The model with the highest metrics, "Rec128_800+3200", *is highlighted in bold.*

No.	Model Name	sMOTSA	MOTSA	MOTSP	IDS	MODSP
1	Rec64_600+1200	-14.37	-7.61	65.18	80	81.60
2	**Rec128_800+3200**	**-9.51**	**-8.17**	**66.58**	**19**	**93.85**
3	Box80_800+2400	-28.43	-21.97	63.47	71	82.54
4	Box160_1000+2400	-75.78	-66.42	64.75	129	80.08
5	BoxApp128_200+1200	-55.12	-46.70	65.11	155	79.92

This grape bunch dataset presented a real, but very challenging environment for object detection and tracking due to the severe sunny conditions, which are common in traditional vineyard regions, such as southern Europe. Figure 4.6 presents the grape bunch prediction using the model "*Rec128_800+3200*", the one with the highest MODSA metrics. The white rectangles indicate false positives in the form of leaves detected as bunches. As can be observed, it is also quite difficult for the human eye to distinguish between grape bunches and surrounding vegetation. Moreover, in the example provided in Figure 4.6, there are multiple vine rows, complicating the algorithm's detection of bunches in the closest row.

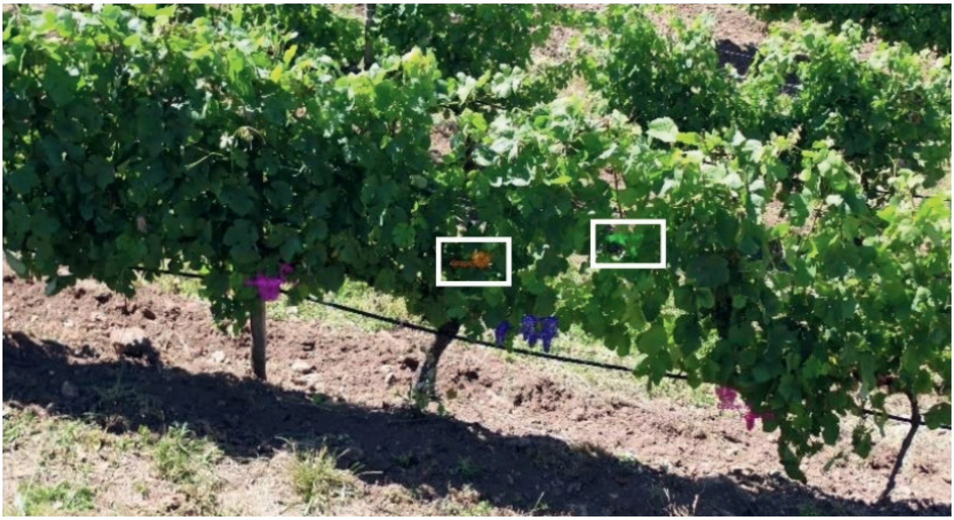


Figure 4.6. Grape bunch predictions using the model Rec128_800+3200. *The white rectangles indicate false positives.*

4.3.2 Berry detection

The detection results on the berries are displayed in Table 4.4. Four models were trained for berry detection. The first two, starting with "*YO*" were trained with YOLACT, whereas the remaining two ("*SE*") were trained with Spatial Embeddings. The numbers provided after the model name indicate the total number of training epochs, which were 80.000, 1.500 and 2.300, respectively. It can be observed that the required time to train the models varied significantly from YOLACT to SE models. Because of resource limitations, YOLACT models were trained with lower batch sizes (2 and 8, respectively).

Table 4.4. Configurations of the four models trained with YOLACT (models 1 and 2) and Spatial Embeddings (models 3 and 4). The YOLACT models are trained in two stages. The SE models are trained in three stages.

No.	Model Name	Time (h)	Batch size	Epoch
1	YO_80000_original	~ 672 (26 days)	2	~ 80,000
2	YO_80000_downsized	~ 437 (18 days)	8	~ 80,000
3	SE_1500	~ 40	32	400+600+500
4	SE_2300	~ 80	32	600+900+800

Table 4.5 presents the mean average precision of all the models trained. The low metrics can be explained by the challenging environment that surrounds each berry (Figure 4.7). The metrics shown in Table 4.5 indicate that SE models outperform YOLACT. There is a lack of "Box" evaluation metrics for SE since the algorithm does not generate bounding boxes. Comparing the two YOLACT models, it can be observed that the model lead to lower mAP_{50} results due to the downsizing of the images.

Table 4.5. Berry detection metrics for both YOLACT and Spatial Embeddings models. In the case of SE, bounding boxes are not available and hence, only mask evaluations are provided. The best model of YOLACT and SE are highlighted in bold.

No.	Model Name	mAP_{50}	
		Box	Mask
1	**YO_80000_original**	**0.68**	**0.41**
2	YO_80000_downsized	0.02	0.01
3	SE20_1500		1.82
4	**SE20_2300**		**2.42**

Figure 4.7 depicts how the model *"YO_80000_original*" detected berries from a full-size image (4096 x 2160). The predictions contained false positives, which are depicted with the dots sprinkled throughout the image. However, there were also high-quality detections, which are depicted by the small bounding boxes around the grape clusters. The main challenge of berry detection was largely due to the size of the detections compared to the images. Each berry represented 4-12 pixels, compared to the 4096 x

2160 pixels of the full image. Overall, the model was able to correctly detect the berries in the bunch. However, there was a significant number of false detections, which lowered the model's performance.

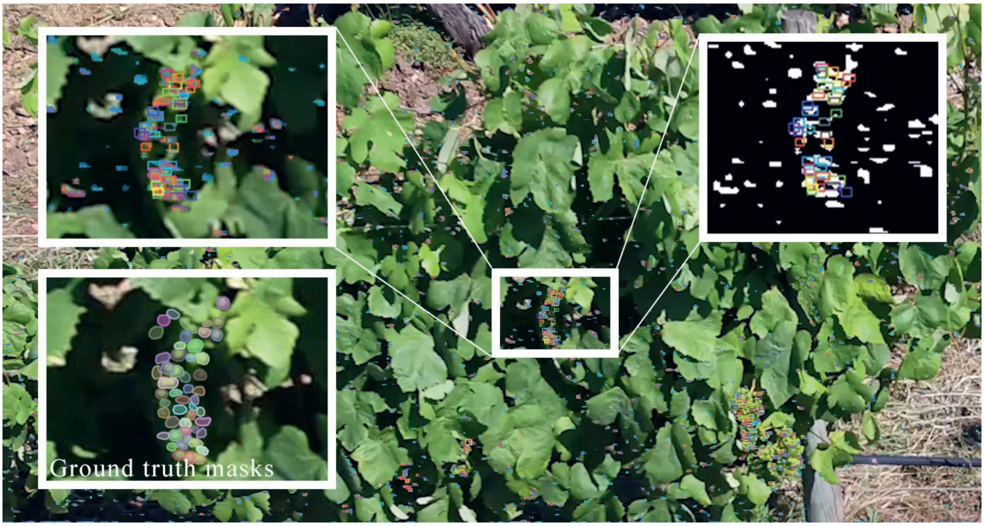


Figure 4.7. YOLACT detection of berries. On the top left it is zoomed in with the predicted grape masks, and in the bottom left with ground truth masks.

Figure 4.8 indicates the workflow that Spatial Embeddings conducted to determine the berry predictions. Spatial Embeddings was trained to detect grape bunches only in the lowest part of the canopy since it is the area in which bunches develop (Reynolds, 2015). There were false positives in the lowest part of the canopy because the algorithm predicted every pixel that had a similar seed map size as a berry. Since the environment was similar in colour to the berries, and the berries had a small size compared to the whole image, there were parts of the image that were mistaken for berries.

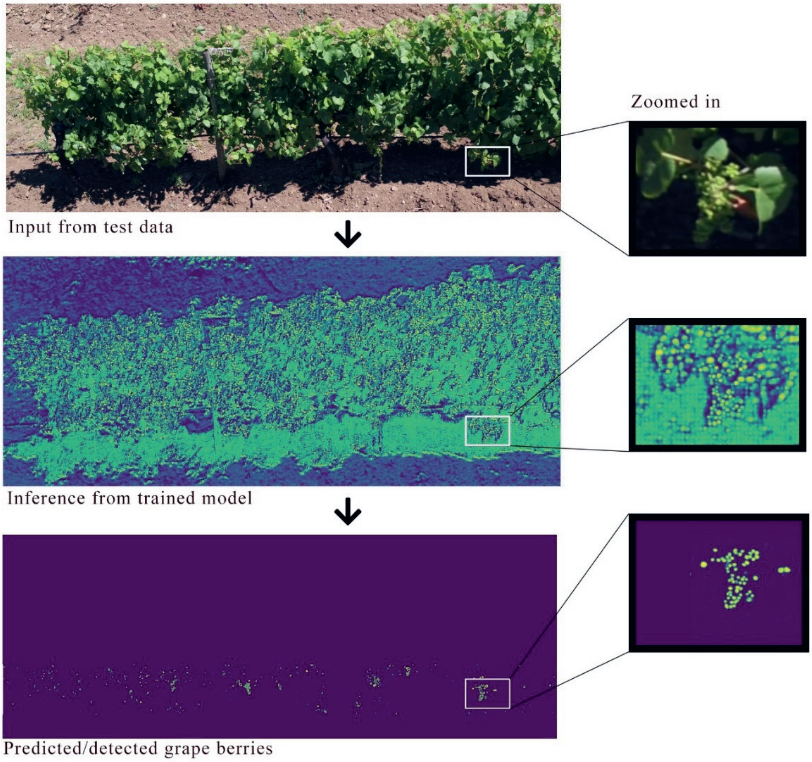


Figure 4.8. Spatial Embeddings process to properly detect berries. On the right side, zoomed-in snapshots to better visualise each of the steps that take place in a bunch to detect the berries it contains.

4.3.3 Grape bunch phenotyping

A comparison of the bunches as seen in the video and the bunch mask as detected by the algorithm is provided in Figure 4.9. The phenotyping traits of the shown bunches were automatically extracted, which are discussed in the rest of this section. It can be observed that for Bunch 3, two bunches were identified as one and hence, the phenotyping measurements obtained differed from the ground truth values.

Figure 4.9. Grape bunch video snapshots (first and third column) and bunch mask detections obtained with PointTrack (second and forth column).

The algorithm is able to properly detect the grape bunches, thus, the next steps correspond to extracting phenotyping traits of each bunch, starting from a comparison between their predicted and labelled size, and followed by the obtention of OIV levels for each of them. Figure 4.10 shows the comparison between the ground truth measurements of each bunch's dimensions (length, width, and shape) and the predicted measurements obtained with the two methods already explained (mask size and rotating the mask). It can be observed that the latter methodology proposed had a higher correlation and lower RMSE (R^2 = 0.62, RMSE = 32.5) compared to the method of extracting the phenotyping traits with the mask size (R^2 = 0.47, RMSE = 37.7).

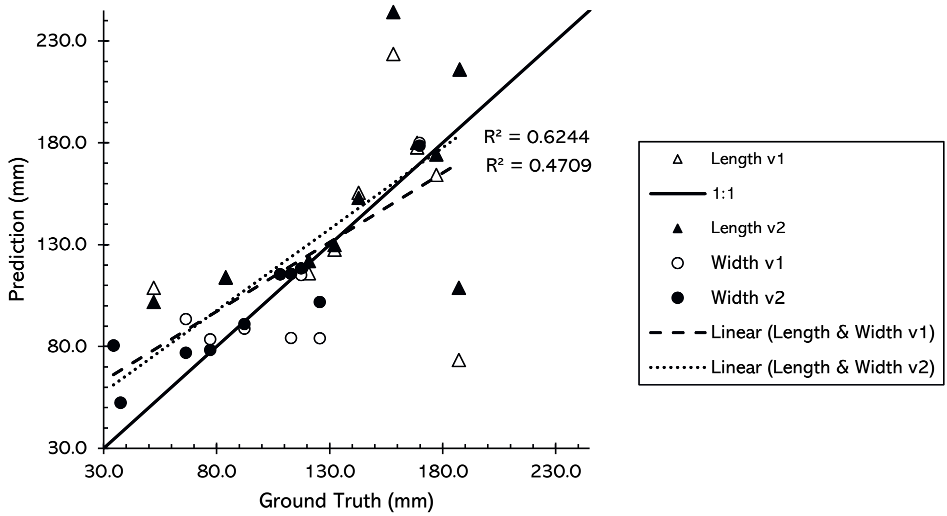


Figure 4.10. Correlation between the ground truth measurements of the grape bunch dimensions (length, width, and shape) and the predicted measurements using two methodologies (1-obtaining the phenotyping traits based on the mask size, and 2- rotating the mask to the largest length of the bunch and obtaining the dimensions after the rotation).

Once it is identified that the second proposed methodology leads to better results in bunch size compared to ground truth values, the comparison between OIV levels is assessed. Since the mask-rotation methodology obtained more accurate results than the first process, that method was considered in the rest of the study. A comparison table between the ground truth OIV category of each grape bunch and the predicted levels following the mask-rotation methodology is provided in Table 4.6, where every row represents each single bunch shown in Figure 4.9. The GT values correspond to the number of berries that were annotated and hence counted inside each grape bunch. However, it is important to remark that only visible grapes, meaning that they are seen from a front view, were annotated.

It can be observed that for most of the cases, the bunch dimensions were properly classified, meaning that both ground truth and prediction have the same OIV level, for instance, level 3 in both cases (3/3). OIV 202 and OIV 203 have 5 levels (International

Organisation of Vine and Wine, 2009) and hence, the legend is split into 5 categories to indicate the number of in-between misclassified levels (1 to 5). For the case of OIV 208, there are only 3 levels, and therefore, a misclassification of 1 level was already penalised as if they had 2 misclassified levels, for instance, GT level 2 and the prediction category 3 (2/3) is shown in orange instead of light yellow.

Table 4.6. Comparison table between the ground truth and the predicted OIV levels of each grape bunch. Each row represents one grape bunch, corresponding to Figure 4.9. In green, the cells that were classified as the same level for GT and prediction. The scale informs about the difference in level between ground truth and prediction. In the case of OIV 208, because there are only 3 possible levels, a difference of 1 level is classified as 2 missed levels.

	Ground Truth / Predicted levels		
	OIV 202	OIV 203	OIV 208
Bunch 1	7 / 7	5 / 5	1 / 1
Bunch 2	5 / 5	3 / 3	2 / 2
Bunch 3	5 / 7	7 / 7	1 / 1
Bunch 4	3 / 3	1 / 3	1 / 1
Bunch 5	7 / 5	5 / 5	2 / 2
Bunch 6	1 / 3	1 / 5	2 / 2
Bunch 7	7 / 3	7 / 5	3 / 2
Bunch 8	5 / 5	3 / 3	2 / 2
Bunch 9	5 / 5	5 / 5	2 / 2
Bunch 10	7 / 5	5 / 5	2 / 3

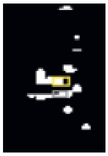
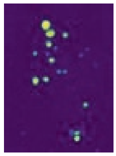
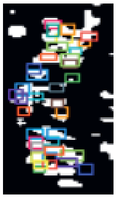
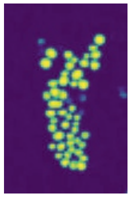
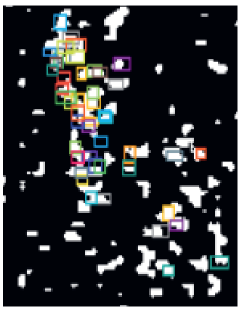
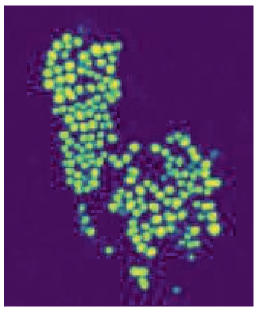
Levels
0
1
2
3
4

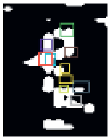
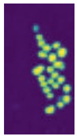
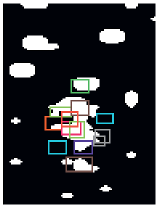
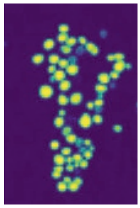
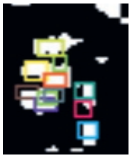
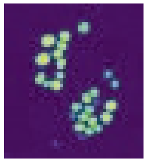
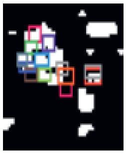
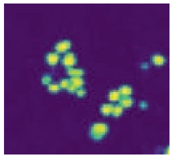
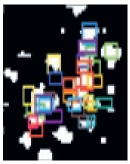
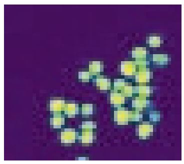
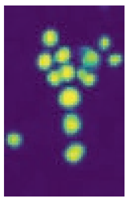
4.3.4 Berry phenotyping

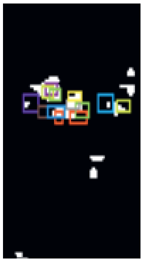
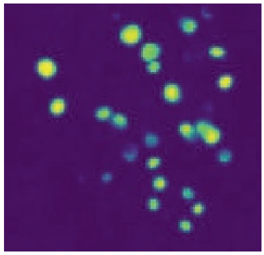
The individual berries within each of the ten grape bunches shown in Figure 4.9 were manually annotated and the two instance segmentation algorithms were used to identify and count the number of berries present per bunch. Table 4.7 provides a visual representation of the detected berries using YOLACT and Spatial Embeddings, along with the ground truth number of berries that were manually labelled. It can be observed that, in general, Spatial Embeddings provides a better estimation of the berries inside each bunch, and also a better reconstruction of the shape of the bunch filled with berries. Bunch 3 includes two bunches in the same instance and hence, it can be observed that the berry count is divided into the left and right bunches to provide a better comparison between models. To determine how accurate the models were compared to the ground truth counts, an estimation ratio was calculated. Spatial Embeddings is the most accurate model for berry detection. All berry counts were better estimated using Spatial

Embeddings compared to YOLACT. Bunches 3 right, 4, and 8 had less than 5% deviation from the ground truth values. Nevertheless, the highest accuracy for YOLACT was on Bunch 7, with a 7% deviation from the annotated value. Spatial Embeddings proved to assess the berry counting more accurately (79.5%) than YOLACT (44.6%). It has been observed that Spatial Embeddings better predicts the amount of berries per bunch and hence, those predictions were used in the rest of the study.

Table 4.7. Berry detection and count within each grape bunch. The second column indicates the number of berries that were manually annotated per bunch and the following two columns are the prediction of the number of berries per bunch using the two instance segmentation algorithms (YOLACT and Spatial Embeddings) along with the percentage of berry count accuracy.

ID	**Ground Truth berry count**	**YOLACT count and estimated amount**	**Spatial Embeddings count and estimated amount**
Bunch 1	33	2 (6%) 	10 (30%) 
Bunch 2	43	35 (81%) 	47 (109%) 
Bunch 3	Left: 68 Right: 56 Total: 124	Left: 39 (57%) Right: 7 (13%) Total: 46 	Left: 79 (116%) Right: 58 (104%) Total: 135 

Bunch 4	22	10 (45%) 	23 (105%) 
Bunch 5	45	13 (29%) 	39 (87%) 
Bunch 6	31	11 (35%) 	21 (68%) 
Bunch 7	15	14 (93%) 	16 (107%) 
Bunch 8	21	31 (148%) 	22 (105%) 
Bunch 9	21	9 (43%) 	11 (52%) 

Bunch 10	46	13 (28%) 	19 (41%) 

Once it is corroborated that the algorithm, especially Spatial Embeddings, can identify each individual berry from the detected bunches, several traits such as the length, width, and shape of each berry are extracted and compared with the ground truth values, which were manually counted in the image and then labelled. The correlation between the ground truth measurements of the number of berries and the predicted values is provided in Figure 4.11. There is a high correlation (R^2 = 0.85) and a low RMSE of 0.65, indicating that the dimensions were accurately predicted.

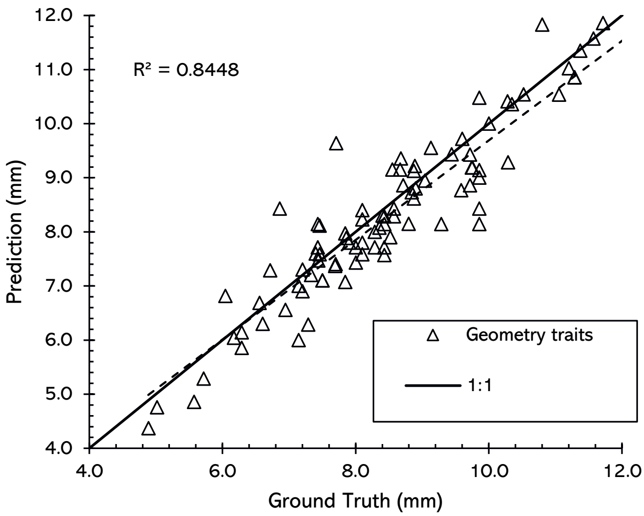


Figure 4.11. Correlation between the ground truth measurements of the berry dimensions (length, width, and shape) and the predicted measurements.

Table 4.8 which provides a comparison table between the ground truth OIV levels of the berries and the predicted levels. Each row represents an individual berry. In 84% of the cases, the OIV level predicted was the same as the ground truth level allocated. In the other 16% of the cases, there was only a 1-level difference between ground truth and predictions, for instance, both being classified as level 1 (1/1). Therefore, it can be concluded that Spatial Embeddings provides accurate predictions for berry OIV categorisation.

Table 4.8. Comparison table between the ground truth and the predicted OIV levels of berries. Each row includes the characteristics of an individual berry. In green, the cells that were classified as the same level for GT and prediction. The scale informs about the difference in level between ground truth and prediction. In the case of OIV 223, because there are only 3 possible levels, a difference of 1 level is classified as 2 missed levels.

Ground Truth / Predicted levels		
OIV 220	OIV 221	OIV 223
2 / 2	2 / 2	1 / 1
1 / 1	2 / 2	1 / 1
2 / 2	1 / 2	3 / 2
2 / 2	2 / 2	2 / 1
1 / 1	2 / 1	1 / 1
2 / 1	2 / 2	1 / 1
1 / 1	2 / 1	1 / 1
2 / 2	2 / 2	1 / 1
1 / 1	1 / 2	1 / 1
2 / 2	2 / 2	2 / 2
2 / 2	2 / 2	1 / 1
1 / 1	2 / 1	1 / 1
1 / 1	1 / 1	2 / 2
1 / 1	1 / 1	1 / 1
1 / 1	1 / 1	3 / 3
2 / 2	2 / 2	2 / 2
1 / 1	1 / 1	2 / 1
2 / 2	1 / 1	3 / 3
1 / 1	1 / 1	1 / 2
1 / 1	1 / 1	3 / 3
2 / 1	1 / 1	3 / 2
2 / 2	2 / 2	1 / 2
1 / 1	1 / 1	1 / 1
1 / 1	1 / 1	2 / 1
1 / 1	2 / 2	1 / 1
1 / 1	1 / 1	1 / 1
2 / 2	2 / 2	1 / 1
1 / 1	1 / 1	2 / 2
2 / 1	1 / 1	2 / 2
1 / 1	1 / 1	2 / 2

Levels
0
1
2
3
4

4.4 Discussion

This study was successful in reaching its objectives: 1) to detect and track grape bunches using PointTrack and to detect berries within the identified bunches using two state-of-the-art instance segmentation algorithms (YOLACT and Spatial Embeddings), and 2) to extract phenotypic characteristics of the bunches and berries.

4.4.1 Object detection and tracking

The tracking performance for clusters was insufficient using PointTrack, a state-of-the-art MOTS algorithm. The tracking metrics were negative due to the switches in ID and/or false positives. The model used in the evaluation had a relatively low number of ID switches, which is comparable to the results of Xu et al. (2020), the original authors of PointTrack. Hence, the low metrics problem lies in the predicted false positives. Based on the review and findings of instance segmentation DL techniques by Hafiz & Bhat (2020), there are two reasons why this is the case: (1) the challenging environment, and (2) the large image size compared to the grape clusters.

Concerning the first possibility, the results of this study differed from the findings of de Jong et al. (2022), who tested PointTrack on a dataset of apples on an orchard, which also had the datasets obtained from UAVs. One factor that is quite crucial in why the apple dataset is more accurate is due to the colour of the objects compared to its surrounding environment (Bullinger et al., 2017). Apples have a distinct red colour, moreover, the PointTrack network emphasises a data modality that is based on differentiating the colour of the target object (Xu et al., 2020). On the other hand, the bunches in this dataset are green, with leaves that have a similar shade of green surrounding them. Many studies have brought up the importance of good visual features in distinguishing objects, which puts this as a primary importance for object detection, especially instance segmentation (Garcia-Garcia et al., 2018; Girshick et al., 2014; Zhu et al., 2012). This lack of colour distinction between the target object and the environment hindered the model from correctly detecting grape clusters, despite the many different strategies applied to train the dataset. Most of the current studies implementing DL instance segmentation techniques for grape bunch and berry detection use red grape varieties (Liu and Whitty, 2015; Torres-Sánchez et al., 2021; C. Zhang et al., 2022), which eases the computer vision task of detecting objects based on colour instead of shape. Moreover, many studies work with leaf removal, fully observing the shape of the bunches

(Nuske et al., 2014; Rose et al., 2016; Santos et al., 2020; L. Shen et al., 2023). Nevertheless, in this study, the grape variety is white, complicating the detection of the bunches in such a homogeneous environment. It should be tested if the trained algorithms are capable of detecting grape bunches and berries in a less challenging environment and with red grape varieties. Nevertheless, red grapes are also green before veraison, so algorithms that work properly with white grapes are completely necessary for early assessment. Another strength of this study is that the hardware used was commercial-grade UAVs and cameras, easing winemakers and farm managers to use these technologies to monitor the bunch's growth during the season. Lastly, working with UAVs permits the analysis of a bigger area than with UGV within the same amount of time, which is relevant in big vineyards to reduce the time window from robot inspection to result extraction and decision-making.

In this study, images are of great size compared to the target objects: bunches. As explained by Hafiz & Bhat (2020), training object inference in CNNs is still an issue, due to the inherent way the layers are trained. In fully convolutional networks, higher CNN layers have lower resolutions but more robustness in different illuminations and poses, and on the other hand, lower CNN layers have higher resolutions but are less sensitive to semantic detail (Long et al., 2015). This approach of creating weights in inference directly affects the ability to train on smaller size objects. Due to the small object sizes, the resolution in lower CNN layers is smaller, which results in higher CNN layers having even smaller resolutions, leading to inferior robustness compared to inference with bigger objects.

Regarding the berry detection metrics, it can be observed in Table 4.5 that the mAP_{50} of Spatial Embeddings is 5.9 times higher than the YOLACT's value. Spatial Embeddings is a proposal-free instance segmentation model that employs a sigma function that could resize instance learning boundaries based on its value, whether it is large or small. As Neven et al. (2019) point out, they treat instance segmentation as a pixel assignment problem, a so-called context-aware detector, which is done by learning a seed map that locates the object centre to learn an optimal clustering region for each object. This is practically achieved through the training of crop instances. The instance crops let the model learn the features of the instance and the surrounding background. However, this convention does not let Spatial Embeddings learn the surrounding environment of the berries. Hence, the many false positives that come around the image is due to the model never being exposed to the background, which in small part defeats the purpose of the 'context-aware' detection system. This problem is not present for the training of other larger objects, i.e., cars, because cars are larger, and its surrounding environment is normally on an urban road. An argument could be made to increase the crop size, so more of the surrounding environment could be learned by the model. However, the training on smaller crops gave a better advantage in shorter training time. To further improve the berry detection, it would be relevant to experiment on training bigger crops, to try and reduce the occurrence of false positives.

4.4.2 Grape bunch and berry phenotyping

With respect to the berry count, Spatial Embeddings performed better than YOLACT, with an average count accuracy of 79.5 and 44.6%, respectively. YOLACT counts range from 0% to 148%, undercounting the berries in most of the bunches. Nevertheless, Spatial Embeddings' ranges from 30% to 116%. It is observed in Table 4.7 that berries inside bunch number 7 are as well counted by YOLACT than SE, which is due to the bunch having very well-defined berries. In general, Spatial Embeddings could segment and detect the berries quite well, except in cases where the berries are totally located under the shade. When the bunch is shaded (Grape 9 and 10), the algorithms do not properly detect the whole bunch. However, when the bunch is partly shaded (Grape 5), the algorithm performs better in the detection of the berries within the whole bunch. It can be argued that the detected bunches that do not have visible berries to count are not valid bunches, since it is also difficult for a person to count them by looking at the image. However, those bunches were included to boost the robustness of the algorithm. It is observed in Table 4.7 that the outer shape of the detections with Spatial Embeddings is more similar to a grape bunch shape than the detections of YOLACT, which have irregular shapes in each prediction. Even if the inside detections of Spatial Embeddings might be missing, having an accurate perimeter of the bunch allows for future possibilities such as object reconstruction, which has widely been applied in medical disciplines (Lin et al., 2021; Singh et al., 2020).

It is important to point out that the counts of the berries only represent one side of the bunch that is visible. Hence, if the model has a 100% estimation accuracy, it is still an underestimation of the real berry counts. Nuske et al. (2011) addressed this issue of berry occlusion by explaining that occlusion is not a problem if there are few false positives, saying that the portion of visible berries could be used to represent the total number of berries from a bunch. Notwithstanding, their further research (Nuske et al., 2014) stated that their method gave difficulty in associating berries with bunches, due to many grapes that have close adjacent bunches.

Concerning the phenotypic traits extracted, the main method is by obtaining pixel counts of the bunch measurements and subsequently converting those numbers to centimetres. Several studies reported reasonable accuracy when phenotyping using pixel conversions to metric (Cabrera-Bosquet et al., 2016; Komyshev et al., 2017; Zhang et al., 2018). The videos taken from a UAV are stable, however, the distance taken from the rows could produce a small variation of angles between different rows. Since the vine poles in the images were taken at different angles, there is a possibility that the pixel measurements are also skewed, generating slight errors between the conversion of different rows. Seethepalli et al. (2020) describe that if the images the pixel conversions would have up until millimetre accuracy if it had at least 10 pixels/millimetre, which is not the case for this study. Hence, a range of ~3 centimetres deviation from the real measurements is expected. In future studies, this issue can be overcome by flying the UAV following a path that respects a constant distance to the target row to decrease this error.

This study offered two methodologies to automatically extract OIV descriptors 202 (bunch length) and 203 (bunch width). The first methodology consisted of extracting the length and width of the mask without considering the orientation of the bunch, which resulted in an R^2 of 0.47 compared to the GT dimensions. Nevertheless, the second methodology proposed, which involves calculating the maximum distance within the bunch mask and rotating the bunch to the vertical angle had a higher R^2 value of 0.62. This second methodology does not need to extract the dimensions of other fruits, for instance, apples and oranges, because of their spherical nature. Nonetheless, because of the non-spherical shape of grape bunches, this methodology was relevant to increase the accuracy of those two OIV descriptors.

This study offers great potential for object detection and tracking for automating the extraction of bunch and berry OIV descriptors. There were two more OIV descriptors (OIV 204 – bunch density, and OIV 222 – uniformity of berry size) that could have been obtained if there was a lower lack of berry detections. OIV 204 consists of defining 5 levels for bunch density (from very loose to very dense). With the amount of detected berries per bunch, the length and width of the berries and the bunch, some threshold can be established to define at which level should the bunch be classified. However, due to the missed berry detections, that OIV descriptor was not provided. Moreover, OIV 222 refers to the uniformity of the berry size and it has two levels: not uniform and uniform. With the results from OIV 223 (berry shape), it can be automatised that if the OIV 223's level is the same for the majority of berries inside the bunch, the result is uniformity in berry size (level 2 of OIV 223). Otherwise, the bunch receives the level 1. Nevertheless, because of the missed detections, this OIV descriptor was also skipped. For future work, when the berry detection metrics are higher, these two OIV descriptors can be provided and automatised.

4.4.3 Future recommendations

Most of the current studies on object detection focus on the computer vision task itself. Nevertheless, the first important step before training the state-of-the-art algorithms is to actually acquire the datasets in the most efficient way focusing on the future purpose of the dataset. For instance, in the case of grape bunch and berry detection, the location of the bunches is crucial to properly plan the path to be followed by the UAV. The size and shape of the leaves, as well as the development of the bunches in vineyards, depends on their position along the stem since it is a function of the node in which it is positioned (Reynolds, 2015). Thus, bunches are always inserted in front of a leaf, up to the tenth bud position or even only up to the eighth, depending on the vine variety, due to various factors such as the inhibitory influence of the apical meristem (Keller, 2020, p. 2). However, since bunches are generated the year before harvest, pruning systems not only regulate vine fruitfulness but also regulate the position of bunches (Eltom et al., 2014), limiting their position to the lower part of the stem or canopy. In the context of commercial vineyards on trellises, the bunches would be located in the bottom part of the canopy, most probably in the first bottom half or the first bottom third of vegetation.

As observed in Figure 4.6, there are videos which count with multiple vine rows, which complicates bunch detection and increases the ratio in size from the target object and the whole frame. Therefore, for future work, it would be important to focus on recording videos in which only one vine row is present, enhancing the recording of the bottom part of the vegetation.

Some authors have already optimised path planning for general purposes (Balampanis et al., 2017, 2016; Raptis et al., 2023; Valente et al., 2013). However, they focus on nadir flights, which have some limitations in agricultural purposes such as disease monitoring and bunch detection. Hence, future work should focus on optimising image and video acquisition for computer vision purposes. In that way, it would facilitate grape bunch and berry detection in the areas in which the likelihood of finding bunches and berries is higher.

4.5 Conclusions

The objective of this study was to obtain measurements of the phenotyping traits of grape bunches and berries within detected bunches at an early stage by applying instance segmentation models with RGB videos obtained with a UAV. This study was carried out in a commercial vineyard presenting leaf-occlusion. The homogeneous background - green berries over green vegetation wall - and the high sunny conditions are challenging factors for bunch and berry detection. The proposed workflow outputs the detected bunch and berry masks along with their dimensions measurements (length, width, and shape) and the OIV levels of those descriptors, which are important for early assessment of yield prediction. Moreover, an evaluation of the berry count compared to the ground truth measurements is provided. Spatial Embeddings proved to assess the berry counting more accurately (79.5%) than YOLACT (44.6%). This work is interesting for early vineyard assessment since red and white grapes are very similar at early stages. For future work, it would be relevant to focus not only on the computer vision task but also on data acquisition to optimise its collection. The dataset containing the UAV RGB videos and the MOTS grape bunch annotations used in this study are available online to boost reproducibility and future work in the field.

Data access

All data collected for this chapter were carefully annotated, post-processed, and uploaded open access to Zenodo. A detailed scientific manuscript was published. This allows other researchers to reproduce the experiment and conduct their own experiments using the collected data.

Ariza-Sentís, M., Vélez, S., & Valente, J.,2023. Dataset on UAV RGB videos acquired over a vineyard including bunch labels for object detection and tracking. Data in Brief, 46, 108848. https://doi.org/10.1016/j.dib.2022.108848

Chapter 5

Theoretical UAV path planning for enhanced grape bunch detection

This chapter is based on:

Ariza-Sentís, M., Vélez, S., Baja, H., Valenti, R.G., Valente, J., 2024. An aerial framework for Multi-View grape bunch detection and route Optimization using ACO. Computers and Electronics in Agriculture, 221, https://doi.org/10.1016/j.compag.2024.108972

Abstract

Typically, commercial orchards and vineyards consist of large fields that encounter similar development phases at once. Thus, it becomes necessary to efficiently fly over all fields to detect fruit and identify their status in a very limited timeframe. For this purpose, UAV path planning plays a pivotal role in agriculture as it enables optimal coverage of agricultural fields, leading to enhanced data acquisition and improved precision agriculture practices, for instance, disease assessment and pesticide application. In addition, DL techniques offer precise image analysis. On the one hand, object detection has been applied to agricultural fields to carry out a wide range of operations, such as detecting apples and predicting yield in vineyards, with higher detection accuracy when the fruits are fully visible. On the other hand, when crops present leaf occlusion, the algorithms face difficulties and are unable to adapt to the specific characteristics of the field. Therefore, this study seeks to address this issue by developing a novel framework to enhance UAV path planning for data collection in vineyards, considering the current biophysical environment. To this end, the proposed framework requires two flights: i) a first flight (survey) to acquire insights on the crop structure and environment, and ii) a second flight using the Ant Colony Optimisation Max-Min Ant System (ACO-MMAS) algorithm to enhance image acquisition by considering multiple angles to overcome partial leaf-occlusion. Further, the optimisation algorithm can potentially boost the acquisition of datasets for fruit detection by considering single and multiple UAVs flying synchronously while ensuring a safe distance between platforms and efficient coverage. The method was tested in two vineyards with different environmental characteristics, increasing levels of difficulty and acquired during two different growing seasons. It improved the length of the computed paths by up to 24%, compared to a base algorithm that considers only the closest point without any optimisation, improving the decision-making processes and resource allocation in crop management.

5.1 Introduction

Remote sensing combined with UAVs has shown to be useful for many applications in the agricultural field, such as fruit identification (Xiong et al., 2020), weed and pathogen assessment (Ali et al., 2023a, 2023b; Valente et al., 2022; Vélez et al., 2023a), yield prediction (Ariza-Sentís et al., 2023b), and path planning (Aggarwal and Kumar, 2020).

Moreover, UAVs provide an advantageous solution for aerial surveying in hard-to-reach areas (Mohsan et al., 2023), such as mountainous terrains or other remote locations.

There is a current trend in precision agriculture focused on woody crops, e.g., vineyards, and fruit orchards, that put the spotlight on DL for fruit detection (Bargoti and Underwood, 2017b; Ganesh et al., 2019; Häni et al., 2020b; Liu and Whitty, 2015; Tian et al., 2019). In those studies, all the attention is driven to object detection, computer vision methods, and their metrics, without considering the optimal acquisition of the dataset, which can potentially increase the detection metrics using the same algorithm. Hence, path planning for optimally acquiring the dataset can be relevant in future object detection studies.

Path planning involves finding a viable route between a starting point and a destination. Nevertheless, the route must consider the obstacles present during the itinerary to avoid collisions between the platform and the surrounding objects, for instance, a tree (Gasparetto et al., 2015). Several path planning algorithms focus on CPP. Nature-inspired algorithms are computational methods designed based on the principles and processes observed in natural systems, such as biological evolution, social behaviour, or physical dynamics. They are used to solve complex problems by mimicking nature's strategies (Vasuki, 2020). These algorithms are particularly effective for optimisation problems in complex search spaces (Tharwat and Schenck, 2021), and some examples include Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Ant Colony Optimisation (ACO) (Dorigo et al., 1996). For UAV path planning for precision agriculture, especially for taking side photos of canopies, ACO can be a better option than GA since it offers high adaptability to replanning (Wakchaure et al., 2023; Yang et al., 2016), typical in agriculture, such as varying canopy sizes or unforeseen obstacles. Moreover, while GA is potent in evolving solutions over large search spaces, premature convergence (if the optimisation problem coincides too quickly, the result is not optimal) is a common issue, and its requirement for extensive iterations for optimal convergence can be a drawback (Katoch et al., 2021). Despite its efficiency and simpler implementation, PSO may falter due to sensitivity to initial conditions and a propensity to get trapped in local optima (Bagheri Tolabi et al., 2021). These limitations allow ACO to perform better and faster in certain scenarios (Chen and Shang, 2021).

Further, UAV path planning encompasses a broad range of applications, including all their individual particularities, such as agriculture. Therefore, it is important to acknowledge the diversity of UAV path planning environments and the necessity of including tailor-made solutions to address specific requirements effectively. ACO and its variant Min-Max Ant System (ACO-MMAS) emulate ant foraging behaviour and have been successfully applied in multi-UAVs flying in dynamic environments (Ali et al., 2023c, 2021) and for minimum time search in uncertain areas (Perez-Carabaza et al., 2018) and obstacle avoidance in various domains (Shafiq et al., 2022), including agriculture (Ali et al., 2022; Bakhtiari et al., 2013, 2011; Nguyen et al., 2016; Rahmalia, 2018).

Many studies have successfully implemented the ACO algorithm for agricultural field operations for both aerial and ground path planning (Englot and Hover, 2011; Garcia et al., 2009; Jennings et al., 2008; H.-J. Wang et al., 2019; Zhang et al., 2010). Moreover, it has been shown the viability of using ACO to create optimal routes for field coverage that can be followed by any farm machinery equipped with auto-steering and navigation systems (Bakhtiari et al., 2011). In those studies, several extensions are proposed to fit broader purposes, such as multi-goal path planning, and considering wind speed. Moreover, ACO-MMAS has been successfully used in several applications (Stützle, 1999; Stützle and Dorigo, 2004) with increased performance for problems related to the Traveling Salesman Problem (TSP), as is the case of the current study. Further, it has been demonstrated that ACO-MMAS is a promising method to attain the goal efficiently (in terms of the robot travel distance) and to optimise the pathway for obstacle avoidance even in unknown scenarios (Luo et al., 2019; Santos et al., 2016).

The optimisation of aerial path planning is crucial in robotics and AI since the low autonomy of aerial vehicles requires that all actions take place within the minimum amount of time (Aggarwal and Kumar, 2020; Oksanen and Visala, 2009). To that extent, several factors must be considered to reach an optimal route for a UAV, such as the path length, the flight time, and the number of turning points (Kumar and Kumar, 2023; Valente et al., 2013). All of them are related to the energy consumption of the platform since it is a limiting factor of the UAV mission (Alyassi et al., 2023).

UGVs have been used to capture the side of the canopy in the case of woody crops trained in vertical trellis (Roure et al., 2018; Stein et al., 2016). Nevertheless, ground robots face challenges such as terrain slope, soil type, stones, and other obstacles on the ground (Santos et al., 2022, 2021). An advantage of working with UAVs, in contrast with UGVs, is that UAVs do not confront these obstacles in their path planning as they are capable of flying above the ground, which eases their path planning.

Aerial path planning can be executed with either a single UAV or by employing multiple UAVs flying and working simultaneously in a cooperative manner. Involving multiple platforms in the mission allows for a reduction in individual mission time while enabling the coverage and recording of larger areas. This aspect is pivotal as most commercial vineyards comprise large fields that undergo similar development phases at the same moment, for instance, during veraison, which is one of the most critical phases, especially for wine-making (Boss et al., 2018). Consequently, it becomes necessary to inspect all fields within a limited timeframe to detect grape bunches and extract their essential characteristics, for instance, for predicting yield or detecting diseases (Vélez et al., 2023a). In the scenario in which multiple UAVs are involved, each UAV follows an individual path from the starting point to the goal point, working in coordination to cover all the designated target fields. Moreover, when conducting multiple simultaneous flights, it is crucial to consider a safe distance between platforms. This distance is influenced by factors such as the flight speed and the size of the UAV (Zhang et al., 2019). Multi-UAV path planning has already been used in the last years for various applications, including oilfield inspection (K. Li et al., 2020), target tracking (Yao et al., 2016), emergency first responders (Luna et al., 2022), and field inspection in precision agriculture (Valente et al., 2013), among others.

Many authors have studied different UAV path planning patterns. (Balampanis et al., 2017, 2016) studied several methodologies for aerial coverage using multiple UAVs. (Valente et al., 2013) proposed a coverage path planner considering the minimum number of turns to minimise the duration of the whole mission. Recently, (Raptis et al., 2023) presented a low-cost platform that serves for coverage mission planning and further dataset analysis, such as orthomosaic generation and vegetation indices calculation. Nonetheless, to the best of our knowledge, all existing agricultural UAV path planners primarily focus on nadir CPP, mostly for photogrammetry applications (Mokrane et al., 2019; Nolan et al., 2017; Raptis et al., 2023). However, nadir flights, which consist of having the camera on board the UAV pointing directly downward, perpendicular to the top of the vegetation, are not suitable for all types of crops. For instance, in woody crops, such as apple orchards or vineyards (Figure 5.1), fruits are located throughout the canopy or at the sides of the canopy (Ariza-Sentís et al., 2023d). Hence, this positioning makes them partially hidden when observing the field from above (Vélez et al., 2023b). When the purpose of the study is to extract the size of fruits or to estimate yield by counting the number of fruits, acquiring data from the side of the canopy will provide more reliable information (Apolo-Apolo et al., 2020; Zabawa et al., 2020). Consequently, path planning should consider the biophysical environment to adapt the route to the specific characteristics of the agricultural field, that is, consider not only the abiotic factors (such as the topography and the geometry of the plot) but also the biotic conditions (plant growth and vegetation development).

Figure 5.1. Fruit distribution in woody crops (i.e. apple orchards and vineyards). The fruits are usually located at the sides of the canopy. Adapted from (Ariza-Sentís et al., 2023d).

Thus, to ensure the acquisition of reliable datasets, it is critical to carefully arrange the image acquisition process by planning the mission and the path using information extracted from the real biophysical environment. Moreover, even if many object detection and instance segmentation algorithms are currently being used to detect fruits, including grape clusters, it is important to recognise that they are trained under artificial conditions. These conditions encompass various scenarios, for instance, vineyards where leaf removal has been executed prior to the UAV flights to facilitate grape bunch detection (Nuske et al., 2014; Rose et al., 2016; Santos et al., 2020; L. Shen et al., 2023). Nevertheless, leaf removal is an expensive practice and cannot be performed in commercial vineyards for the sole purpose of acquiring side images. Therefore, the grape bunch detection algorithms developed to date are not robust enough to be applied to more challenging and realistic environments.

In order to acquire proper datasets for object detection, several flights are currently needed. For instance, Ariza-Sentís et al. (2023c) executed four flights, one per vineyard row, to record the necessary data to perform grape bunch detection since they did not use any optimisation algorithm prior to data acquisition. However, with the proposed method, only two flights are demanded, which cover multiple vineyard rows. Considering all factors, it is crucial to consider the biophysical environment of the agricultural field when planning UAV paths. Aiming to acquire optimal data for fruit detection in leaf-occluded fields, the mission should involve capturing the crop rows from multiple viewing angles, specifically from the side (Figure 5.2).

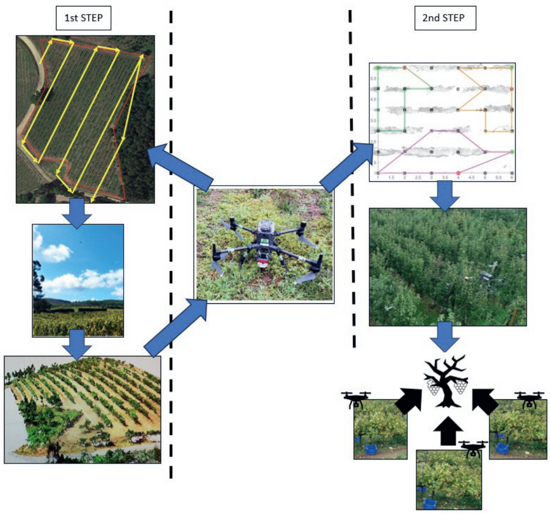


Figure 5.2. Proposed Framework for Vineyard Monitoring. The two-flight system integrates plot geometry for path planning in the first flight, followed by a photogrammetric model creation capturing the biophysical reality of the vineyard. This model is used for the second flight's planning, focusing on missing plants, their condition, and multi-angle imagery of each plant for enhanced fruit data collection.

This paper introduces a framework for improving fruit detection in vineyards trained in vertical trellis without leaf removal by emphasising advanced path planning that incorporates multiple viewing angles and information about the actual biophysical environment. The primary motivation for this research:

i) Establishing an innovative path planning strategy that enhances fruit detection in vertically trained vineyards, considering the dynamic nature of plant growth over time.
ii) Implementing a methodology that utilises multiple perspectives to minimise errors in fruit counting due to leaves obstructing the view.
iii) Developing a workflow suited for both individual and multiple UAVs operating in tandem above the field, consisting of an initial survey flight to gather key field characteristics and a follow-up flight focused on improving fruit detection.
iv) Employing the Max-Min Ant System (ACO-MMAS) for optimal path determination in fruit identification tasks, compared to the Nearest Neighbour Search, with the possibility of future research exploring other fitting path planning algorithms.

The remainder of this paper is structured as follows: Section 2 includes the Materials and Methods utilised in this research, including a detailed explanation of the algorithm implemented. Section 3 encompasses the Results obtained with the proposed algorithm in contrast to a base algorithm that solely accounts for the nearest point, without incorporating any optimisation. Section 4 encompasses a detailed Discussion covering the novelty of this research, its advantages, limitations, and future work. Finally, Section 5 includes the Conclusions of the study.

5.2 Materials and Methods

5.2.1 Vineyards

The study was conducted utilising two different vineyards located 175 meters away from each other (Figure 5.3). Both agricultural fields belong to a commercial vineyard *Vitis vinifera* cv. Loureiro, situated in 'Tomino, Pontevedra', Galicia, Spain. The vineyards are owned by 'Bodegas Terras Gauda, S.A.' Both vineyards have a distance between plants and rows of 2.5 × 3 m. The information of the first vineyard (B9) (X: 517186.7, Y:

4645072.3; ETRS89 / UTM zone 29 N) was acquired in 2021 during a survey flight conducted at a height of 30 meters above ground level (AGL). The second vineyard (B7) (X: 517186.12, Y: 4645077.47) was surveyed in 2022, with the flight altitude set at 20 meters AGL.

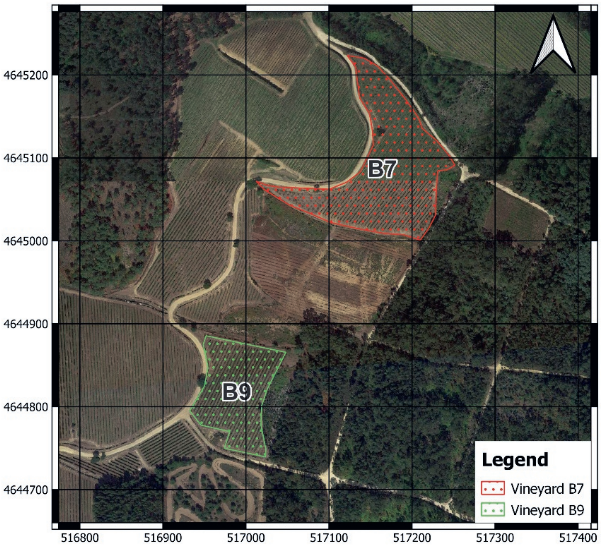


Figure 5.3. Location of vineyards B9 (in green) and B7 (in red). Coordinates in ETRS89 / UTM zone 29N (EPSG: 25829).

5.2.2 Enhanced UAV path planning framework for fruit detection

The biophysical environment needed to be considered to generate an optimal path for fruit detection in a specific agricultural field. Figure 5.4 illustrates the workflow adopted in this study to arrange the UAV path. The workflow started by taking raw RGB images as the input. These images are processed via photogrammetry to generate a 3D point cloud. This step used Agisoft Metashape Professional software, v1.7.6 (Agisoft LLC, St. Petersburg, Russia). The 3D point cloud was then used to create the Digital Surface Model (DSM) and the Digital Terrain Model (DTM). By subtracting the DTM from the DSM, the Canopy Height Model (CHM) was obtained, which provided information regarding the height of the vegetation. In this particular study, in vineyards with cover crops and surrounded by forest, any area with a height between 0.5 and 2 meters was considered to contain the crop of interest (vine plants). All the data processing and path plan design were carried out using QGIS software (version 3.22. X, QGIS developer team 2022) and

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MATLAB® Release R2022b (The MathWorks Inc., 2022). The code written in MATLAB has been made available to the scientific community (Valente et al., 2023).

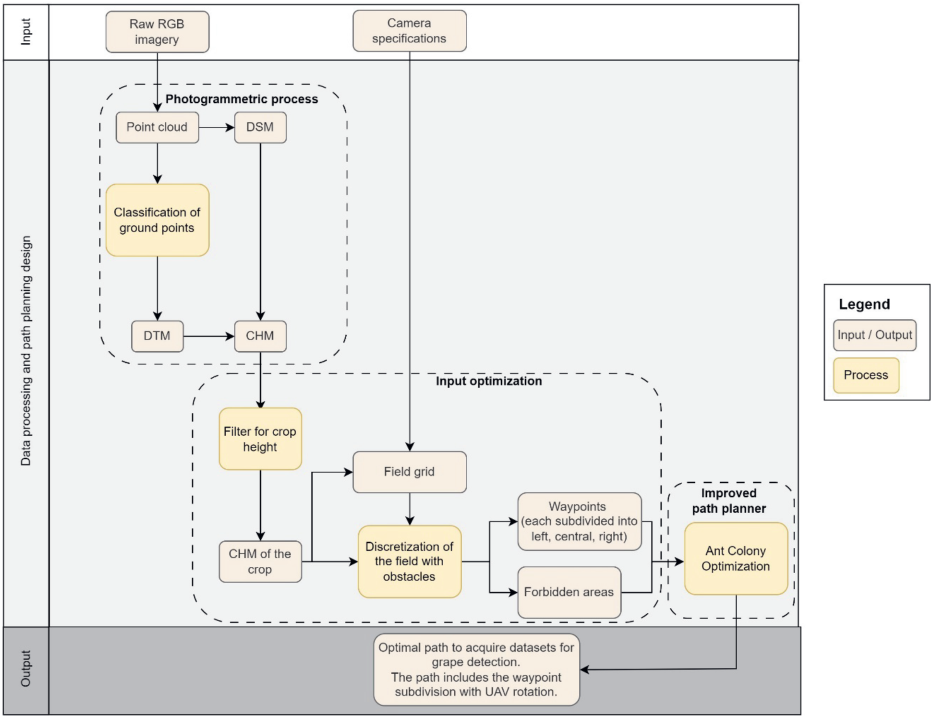


Figure 5.4. Workflow of the proposed methodology to design the path planning for optimal data acquisition. The required inputs are the raw RGB images as collected by the UAV and the field grid, considering the distance between rows and plants. The output is the optimal path, designed using ACO, specifically made for the field in which the data is acquired.

5.2.2.1 Survey flight: identification of biophysical parameters

During the UAV path design process, it was essential to distinguish between two types of regions: (1) the regions of interest, which were designated as waypoints along the path, and (2) forbidden areas, which were regions without agronomic interest, for instance, areas with vine plants' deficiencies, or areas with danger for the UAV, such as zones surrounded by trees, high-voltage towers, and areas where people were actively engaged in activities such as spraying, pruning, defoliating. Missing plants are recognised as substantial deviations in vine height, resulting in a discontinuity in the CHM. When such deviations occurred, the corresponding area was designated as a forbidden area (indicated by the red boxes in Figure 5.5). Conversely, if no significant deviations were observed, the area was labelled as a region of interest (indicated by the white boxes in Figure 5.5).

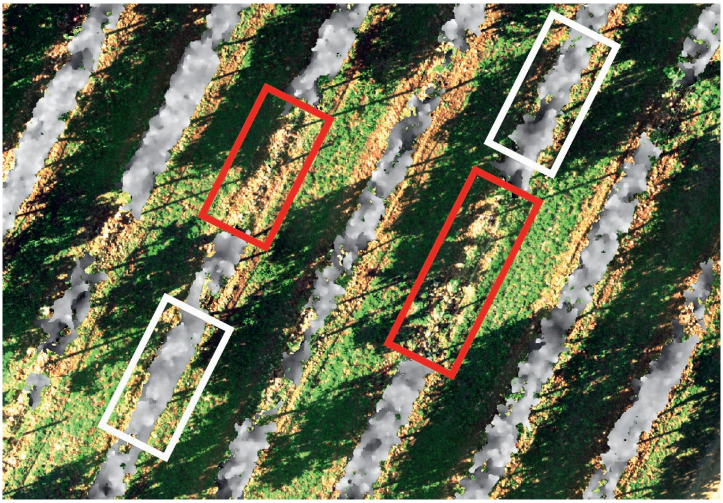


Figure 5.5. Canopy Height Model of the vineyard (in grey tones) over the orthomosaic of the field (in RGB). The white boxes illustrate the areas in which there are vine plants. The red boxes indicate where plants are missing or not growing properly since the orthomosaic shows the soil and/or cover crop instead of the CHM.

5.2.2.2 Determination of the field grid and waypoints

In order to determine the size of the field grid, several parameters were required (Equation 1). The height of the flight was defined by computing the maximum value of the CHM over the whole area to be flown. A vertical security distance of 0.5 meters was also incorporated to prevent any potential collisions with small branches. The focal length and sensor size are specific parameters for each sensor and can be obtained from the camera model specifications. In summary, the horizontal grid size, measured in meters, determined the extent of canopy coverage. This refers to the horizontal area of the crop captured by each image (as depicted in Figure 5.6), which was crucial for determining the number of images required per crop row or region of interest. The relationship between the grid size (d), flight altitude (h), sensor size (d_s), and focal length (h) can be expressed by the equation:

$$d = \frac{h * d_s}{f} \quad (1)$$

where d is the canopy coverage (m), h is the UAV height (m), d_s is the size of the camera sensor (mm), and f is the focal length (mm).

Moreover, to record the entire canopy or more specifically, the region in which grape bunches are more likely to be located, it was necessary to tilt the sensors using the following formula:

$$tg\ (\alpha) = \frac{h}{r} \tag{2}$$

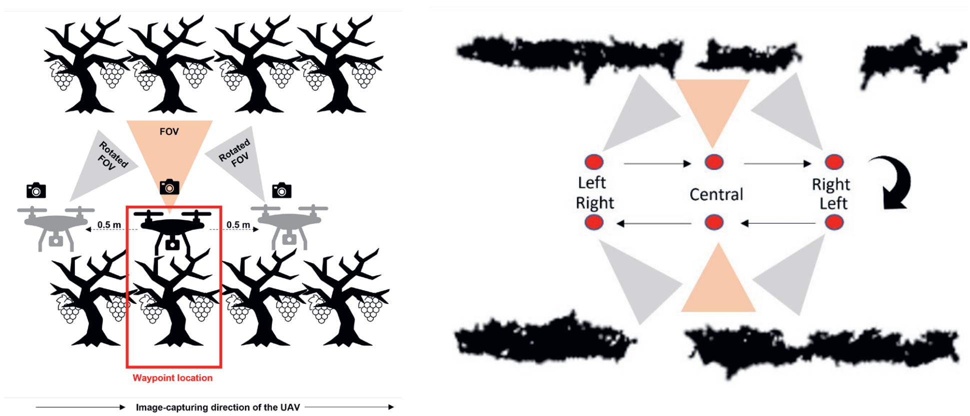
where α is the tilted angle with respect to the horizontal plane (in degrees), and r is the distance between vine rows (in meters), which is a fixed parameter because it was defined when the vines were planted.

In this study, the sensor used to carry out the side missions aimed to enhance fruit detection was the Micasense ALTUM-PT (AgEagle Sensor Systems Inc., Wichita, Kansas, USA), which features a camera sensor size of 7.12 mm (horizontal) and 5.33 mm (vertical), and a focal length of 8 mm. The CHM for vineyard B9 reached a maximum value of 1.8 meters, resulting in a UAV height of 2.3 meters (because of the vertical security distance). By applying the formula presented in Equation 1, the horizontal dimension of the grid was determined to be 2.05 meters, and the vertical dimension, which consists of using the vertical size of the camera sensor, corresponds to 1.53 meters. Therefore, each image has a coverage area of 2.05 x 1.53 meters, resulting in 3.14 m^2. Additionally, to capture the bottom part of the canopy, which is where grape bunches develop (Zabawa et al., 2019), the camera was tilted 37.5 degrees downward with respect to the horizontal plane (Ariza-Sentís et al., 2023a). As a result, the vertical dimension of the grid was not relevant since the camera was already tilted to record the region of interest within the canopy.

Figure 5.6. The yellow squares represent the area covered by each image taken, considering the UAV height and the specifications of the camera, such as focal length and sensor size. The red box indicates the area in which grape bunches develop.

After determining the horizontal distance of the grid, this length was used to generate a nadir grid that was superimposed onto the Canopy Height Model (similar to the squares in Figure 5.5). Zonal statistics were then performed to count the number of CHM pixels present in each cell. Cells containing less than 10% of the maximum pixel count were marked as forbidden areas. It was manually determined that the grid did not cover a representative part of vine plants below that percentage. Conversely, cells meeting this condition were marked as waypoints, representing locations to be visited by the UAVs. This step was crucial to discretise the agricultural fields into waypoints (called cities in the ACO-MMAS algorithm) and forbidden areas.

It is important to note that, since vineyards hold two sides of the canopy, the UAV needed to take pictures of both sides. As can be observed in Figure 5.7b, while the UAV flew on top of a row, the UAV platform rotated to capture pictures of the two adjacent rows, provided that there were vine plants on both sides. However, if one side had some missing plants or if there were no more plants, for instance, in the last row, that side was not considered a waypoint, and hence, the UAV only took pictures of the side with vegetation. Several articles have claimed the problem of leaf-occlusion in woody crops, which consists of the fruit being partly or fully hidden by leaves (Gongal et al., 2016; Kestur et al., 2019; Lu et al., 2018). In the case of partly hidden, there is an optimal angle from which the fruit is less hidden. However, for fully hidden fruits, for instance, wrapped by a leaf, there is no optimal angle for its detection. Since in this study, the experiments were conducted in a commercial vineyard, no leaf removal was performed, and hence, the vineyard presented leaf occlusion. Figure 5.7a illustrates one of the novelties of the proposed methodology to solve the leaf occlusion problem and boost the detection of grape bunches. Each waypoint was divided into three sub-waypoints to automatise the entire procedure, each of them having the desired camera angle. To optimise the path length, the UAV automatically flew to the left waypoint, took a picture, moved to the central waypoint, proceeded with the picture, and finally went to the right waypoint and took the last picture. Afterwards, it flew to the next left waypoint, continued with the central location, moved to the right waypoint, and so on (Figure 5.7b). The distance between the left waypoint and the central waypoint was 0.5 meters, the same as the space between the central and the right waypoint. This value of 0.5 meters was calculated as ¼ of the horizontal dimension of the grid (around 2 meters), which allows observing the grape bunches at three different positions defined as ¼, ½, and ¾ of the horizontal distance. The optimisation of the UAV path was executed using the ACO-MMAS algorithm, which is further explained in the next subsection. Lastly, once the trajectory was optimised, including all the waypoints and their triplet subdivision (incorporating the UAV rotation for the left and right waypoints), the route was exported as a KML file to be interpreted as a mission by the UAV.



(a) (b)

Left Central Right

(c)

Figure 5.7. UAV flying on top of the canopy of the adjacent row to record the sides of the vineyard row of interest. (a): Each waypoint location is subdivided into the left, centre, and right waypoints. (b): Waypoint recording in case both sides of the canopy are of agricultural interest. (c): Images showing the three-perspective objective of the path planner, which allows different perspectives of the same grape bunch.

5.2.3 Ant Colony Optimisation algorithm

The natural environment and, more particularly, animal behaviour have inspired computer scientists and engineers to develop many of the tools that we use daily in the fields of aerial and marine transportation, communication, and learning, by implementing mathematical models that extrapolate the main ideas to reach the desired goal. The ACO algorithm (Dorigo et al., 1996) is a heuristic approach inspired by the cooperative behaviour of ants when foraging, finding the shortest and collision-free path.

The theory behind ACO is that when foraging, ants release pheromones on their path, which the following ants use to choose a suitable route based on the number of pheromones found. The higher the concentration, the more likely that ants choose that route. Nevertheless, pheromones evaporate, causing a decrease in their concentration. The path that receives the fewest visits experiences the fastest evaporation of pheromones due to its lower concentration. Conversely, the most frequently visited path, often one of the shortest routes, accumulates a higher concentration of pheromones, dominating other paths. As a result, ants are inclined to move towards shorter paths, driven by the higher pheromone concentration they offer (Yu et al., 2017).

Once the reasoning behind ACO is introduced, the learnt knowledge can be applied to the problem of CPP since ants generate and follow a path from a starting to an endpoint while avoiding the area that contains obstacles (forbidden areas). Moreover, because ants release pheromones, they remember the zones that have already been visited, and those are neither repeated nor overlapped. Consequently, ACO is a suitable algorithm for agricultural CPP.

5.2.4 ACO applied to agricultural UAV path planning

As this study addresses an optimisation challenge involving area coverage with obstacle avoidance, a variant of the TSP, tailored for multiple UAVs but adaptable to diverse farm platforms, the ACO-MMAS method has been selected and adapted as the primary approach for this research endeavour. The reasoning behind ACO-MMAS is shown in Algorithm 1, which started with an initialisation of the pheromones trail, assessed by a matrix that maps all arcs from the search space.

Algorithm 1 ACO-MMAS modified

1: **Initialise** pheromone trails
2: **while** Not Stop Condition **do**
3: Tour construction
4: Set pheromone limits
5: Update pheromones trails
6: **if** some sort of stagnation **then**
7: **Initialise** pheromone trails
8: **end if**
9: **end while**
10: **Return** solution(s)

The pheromone trail in ACO-MMAS can be defined as:

$$\forall(i,j), \tau_{ij} = \tau_0 = \frac{m}{C^{nn}},\ with\ 0 \leq \rho \leq 1 \tag{3}$$

where τ_{ij} is the quantity of pheromone released from point i to j, τ_0 is the initial pheromone concentration, ρ is the pheromone evaporation rate, n is the number of points, and C_{nn} is the cost of a path computed with a nearest-neighbour heuristic.

After initialising the pheromone trail, the Tour Construction starts. In that phase, n ants start building the path of the TSP from randomly chosen initial points (called cities), and they move iteratively from point to point while adding the cities that had not been visited yet. During every stage of construction, each ant k employs a rule called random-proportional rule (GRP) that involves probabilistic action choices to decide the following city. GRP is employed since it facilitates the exploration of neighbouring points by increasing the probability of selecting a solution component with low pheromone concentration (Zheng et al., 2010). Specifically, the likelihood that ant k, situated at city i, opts to travel to city j is defined as the following equation:

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l} \mathrm{N_i^k} [\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}, \quad if\ j \in \mathrm{N_i^k} \tag{4}$$

where $\eta_{ij} = \frac{1}{d_{ij}}$ is a heuristic value available a priori since d_{ij} corresponds to the distance between nodes i and j. α and β represent two parameters that dictate the relative weight or influence of the pheromone trail and the heuristic information, and N_i^k refers to the viable neighbourhood of ant k while located in city i. This set comprises cities that ant k hasn't visited yet, signifying that the probability of selecting a city outside N_i^k is 0.

Through this probabilistic approach, the likelihood of selecting a specific arc i, j rises in accordance with the associated values of the pheromone trail (τ_{ij}) and the heuristic information value (η_{ij}). On the one hand, when $\alpha = 0$, there is a higher probability of selecting the closest cities, resembling a conventional stochastic greedy algorithm (with multiple starting points due to the random distribution of ants across cities initially). On the other hand, when $\beta = 0$, only pheromone amplification operates, excluding any heuristic bias. Therefore, it is important to select the appropriate values of α and β for each specific study case.

Moreover, each ant k has a memory that stores the sequence of already visited cities, along with the order they were visited. This memory serves the purpose of determining the feasibility of neighbourhood N_i^k as shown in Equation 4. Further, that memory enables ant k to calculate the length of the tour constructed so far and to retrace the path to deposit the pheromones.

When all the ants had finished creating paths, the pheromones were updated by considering the evaporation rate.

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad \forall (i,j) \in \mathrm{L} \tag{5}$$

To avoid stagnation, a lower and upper limit $(\tau_{min}, \tau_{\max})$ were imposed on the pheromone trails, which are given by:

$$\tau_{min} = \frac{\tau_{max}(1-\sqrt[n]{0.05})}{(avg-1)\sqrt[n]{0.05}}, \quad \tau_{max} = \frac{1}{\rho C^{best}} \tag{6}$$

where C^{best} is the best-so-far and/or iterated-best tour length and avg is the average number of neighbourhoods available for an ant at each step while building a solution. The last step was to reinitialise the pheromone trails after some iterations in case no improvement was added to the current solution. Finally, the stop condition, which could be the computation time, the number of iterations, or the minimum predefined cost, ceased the algorithm.

For this case study, the ACO-MMAS variant was modified in order to reach all the objectives of the project. The modifications were as follows:

(1) The initialisation of the variables was adapted, which included optimisation problem variables and MMAS parameters. These parameters were the number of robots (nr), the predefined starting and end positions, the number of ants, the number of iterations, the pheromone reinitialization condition, and the stop condition.

(2) To initialise the pheromone trail, the nearest-neighbour heuristic was used to compute the cost of the path and to define the pheromone's concentration limit (upper bound).

$$C^{mmas} \leq C^{nn} \tag{7}$$

When the number of UAVs (nr) was higher than 1:

$$C'^{nn} = \frac{C^{nn}}{nr} \tag{8}$$

where C'^{nn} is the upper bound taking into account all the trajectories computed simultaneously.

(3) The computation of the path played a crucial role in allowing the algorithm to converge. In the conventional ACO-MMAS, each ant created a tour, whereas, in the adaptation for this study, each ant scouted as many tours as there were robots (UAVs). In our variant, the final tour was the sum of the lengths of all tours generated by all the individual ants (Figure 5.8). Moreover, each subtour had a pheromone memory linked, which did not influence the rest of the tours. In this way, only when the ant had explored the path in its whole, the next ant started scouting. Further, the cost of each ant was calculated based on the tour length cost (TLC) and the safe distance cost (SDC), which was the number of times that the safe distance was lower than a threshold. Since the distance between grid cells was constant, it was pre-defined that a value of $\sqrt{2}$ had to be always kept between platforms. This value was understood as the diagonal distance between two cells separated by one map unit.

$$J^k = J^k_{TLC} + J^k_{SDC}, k = 1, 2, \dots, m \tag{9}$$

$$J_{TLC} = \sum C^k_t \tag{10}$$

$$J_{SDC} = \sum d(i, j) \leq \sqrt{2} \tag{11}$$

where J is the cost of each ant, k is the number of ants, C is the length of a tour t, d is the Euclidean distance between two points i and j.

In contrast to the conventional ACO-MMAS, the variant proposed in this study introduced a notable difference regarding the implementation of the Moore neighbourhood, which involves considering the 8-neighbouring cells. The original ACO-MMAS utilised the Moore neighbourhood, which had the disadvantage of potentially causing the tour construction to become stuck due to the neighbourhood limit. This limitation could occur when an ant blocked or closed the tour construction, preventing subsequent ants or even itself from progressing. To address this issue, the proposed modification eliminated the use of the Moore neighbourhood only when no non-visited points were remaining. Instead, the algorithm continued from the closest waypoint. Whenever an ant visited a waypoint, the location was stored in memory and marked as visited. As a result, ants were able to generate a map with the currently available waypoints and update the pheromone trail accordingly.

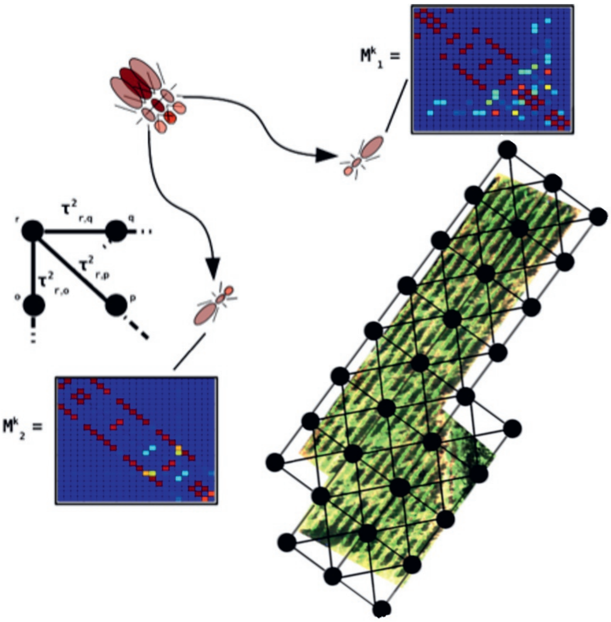


Figure 5.8. Representation of the methodology used by an individual ant to perform the tour construction over a whole agricultural field.

(4) The pheromones limits, as defined in Equation 5, were set before updating the trails. After, the pheromone memory was updated as in ACO-MMAS (Equation 4).

(5) The reinitialization for the pheromones trails was not mandatory but was kept in case the algorithm got stagnant, or the convergence was complicated to reach (Algorithm 1). Hence, the pheromone trail was reinitialised only in the case that the best-so-far cost was equal to or higher than the cost of an individual coverage path.

5.3 Results

The next subsections include a detailed explanation of the results obtained in each step carried out in both the B9 and B7 vineyards. Each vineyard was subdivided into three scenarios with increasing levels of difficulty regarding the density of forbidden areas (low, medium, and high density) to observe the applicability and robustness of the designed path. The low area included three forbidden areas in both vineyards, which represented 8.3% of the total area covered. The middle zone had 6 and 7 forbidden areas for vineyards B9 and B7, respectively, which constituted 16.6% and 19.4% of the whole area. Finally, the high area included had 22.2% of the whole area of interest forbidden, which corresponded to 8 forbidden cities. It can be observed in Figure 5.9 that the higher the level of difficulty, the more vegetation gaps were present in the vineyard. Moreover, the higher the density of the forbidden area, the more complicated the final path becomes (Table 5.1).

5.3.1 Aerial exploration of the biophysical environment

The first step was to perform the exploratory flight to understand the specific biophysical characteristics of the agricultural field. Figure 5.9 indicates the three density areas in which vineyard B9 was divided. The low-density area included rows with very few forbidden areas or areas without agronomic interest. The medium and high-density areas consisted of more areas over which the UAVs were not allowed to fly. As observed, apart from the rows included within each density area, the adjacent rows were also shown since the canopy needed to be captured from both sides. In the case of the high-density area, the extra row below was sparsely vegetated because it was the last row of the vineyard. The part of the adjacent row that was closest to the forest became a forbidden area from which no images could be captured.

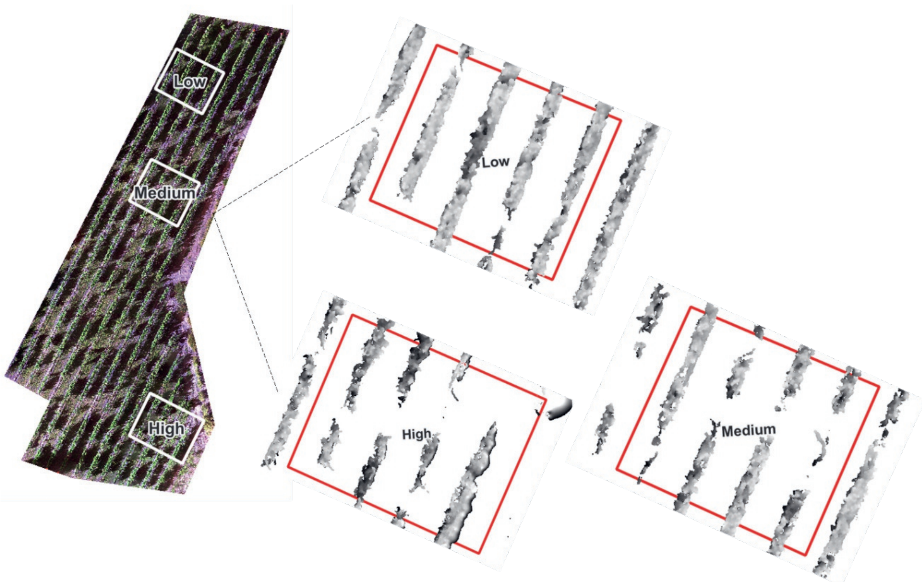


Figure 5.9. Density of forbidden areas in vineyard B9, including an aerial view of the agricultural field with the three zones incorporated (white boxes). The red boxes show the Canopy Height Model inside each density area (High, medium, and low vegetation). In addition, each area includes the CHM of the two adjacent rows from which the canopy will also be captured.

Once the cells with vine plants were known, the next step was to compute the number of waypoints of the field, considering that the vegetation had to be observed from both laterals. The UAV flew over the two inner rows, capturing images from both sides in most cases, as indicated in Figure 5.10. However, in regions where vine plants were present only on one side, the UAV only acquired images of the vegetated lateral. Also, it was marked as a forbidden area in cases with no vine plants or less than 10% of the maximum pixel count. Finally, only images from one side were collected in the top two and bottom two rows, which were the end and extra rows. Figure 5.10a includes the cells captured from the right lateral; thus, the top row is not included since it was recorded from the adjacent lateral (including four orange cells and two red cells). The same applies to Figure 5.10b since it provides the cells recorded from the left lateral; hence, the bottom row is not coloured. Finally, Figure 5.10c displays the waypoint distribution along the six rows, delineating the waypoints recorded from the left (orange), right (orange), or both sides of the canopy (green). Moreover, it includes, in red, the areas without agronomic interest or forbidden regions above which the UAV did not fly.

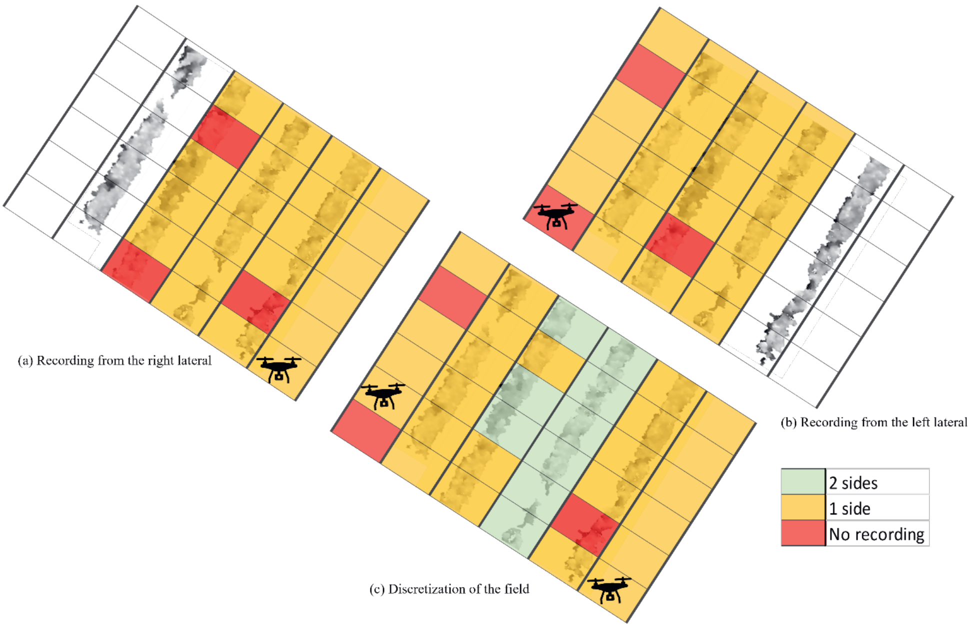


Figure 5.10. Distribution of waypoints along the low-density region. In the background, the Canopy Height Model indicates the four rows of vines. The red cells include the areas without vine plants or with less than 10% of the maximum pixel count. (a) Waypoint distribution as if it was recorded only from the right lateral of the vineyard. (b) Distribution of the field according to the UAV flying from the left lateral. (c) General discretisation of the field considering the collection from both sides. In the front, the waypoints are classified as waypoints that collect images from the two laterals of the canopy (green), only from one side (orange), or an area above which the UAV will not fly (red). As can be observed, the top and bottom rows include only waypoints from one lateral.

5.3.2 Validation

This section presents the results regarding the optimised routes using tailor-made ACO-MMAS. For that, the proposed methodology was applied to each of the two mentioned vineyards and the three levels of difficulty in each vineyard. Hence, there were a total of 6 scenarios considered. Moreover, the metrics of each scenario concerning path length and elapsed time, compared to a base algorithm that did not consider any route optimisation, are introduced.

The waypoint distribution shown in Figure 5.10c was the input of the ACO algorithm. It required to enter the number of rows and columns of the matrix and to mention which were the forbidden cities, above which no trajectory was considered. Moreover, another necessary variable was the number of UAVs that would fly simultaneously since it needed to compute a security distance between platforms in case the number of UAVs was above

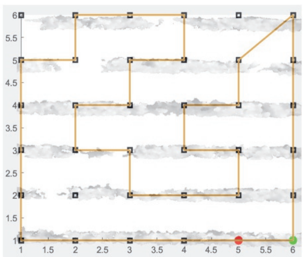
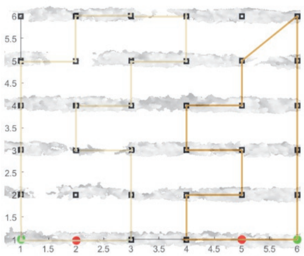
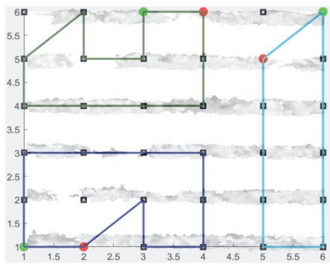
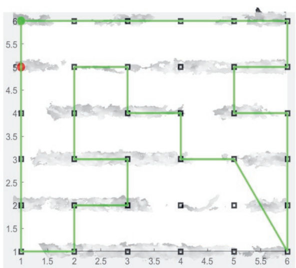
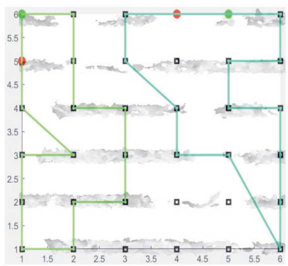
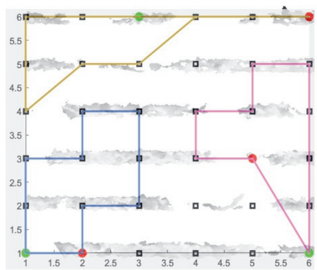
1. Moreover, α, β, and ρ values were also required, which were set to 1, 2, and 0.02, respectively, after several finetuning runs. The last input was the start position, which could be any cell considered a waypoint. The main output of the ACO-MMS algorithm was the route that the UAVs followed, together with a summary of the statistics of the path, for instance, the route length using the ACO-MMS algorithm and the path length if the same route had been computed using the Nearest Neighbour Search (NNS) algorithm since it stands out for its speed and simplicity, especially when quick solutions are essential (Rakotondrasoa et al., 2023). Hence, comparing trajectories helped validate that the proposed ACO-MMAS method could optimise the UAV trajectory.

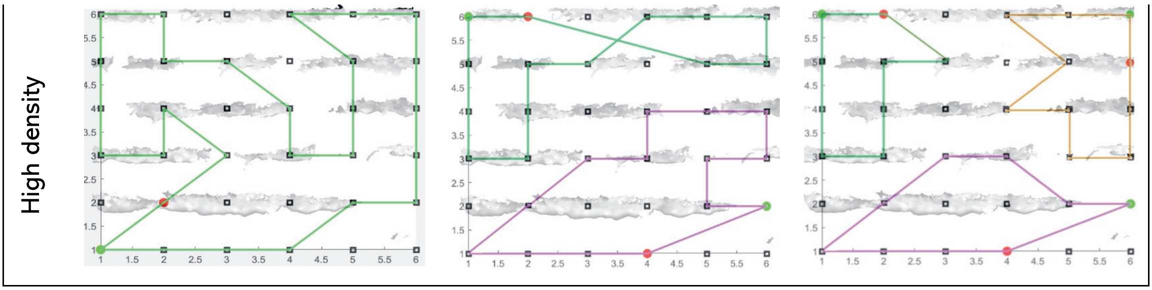
Table 5.1 illustrates an output of the ACO-MMAS algorithm with the three forbidden-area densities of field B9, utilising 1, 2, and 3 UAVs. It designated the most optimal route that began at the pre-defined start position, indicated with a green dot, and ended in a cell near the home position, marked with a red dot. When utilising multiple platforms and operating in high-density areas, routes exhibited distinctive features. For example, some more irregular polygons or paths traversed the same waypoint twice (as seen with 3 UAVs in medium density), especially when compared to low-density routes.

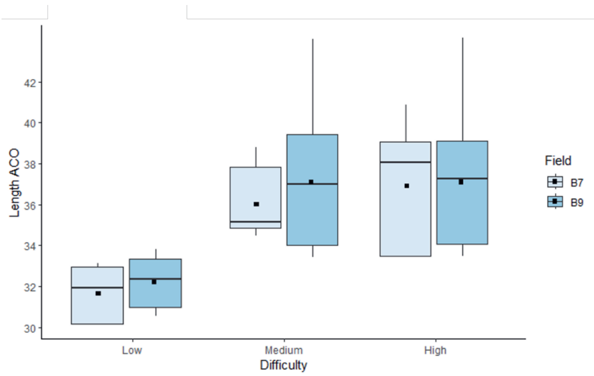
It is important to remark that, as mentioned before, each waypoint was subdivided into left, central, and right waypoints. This subdivision was not shown in the figures to simplify them, but in each case, the UAV started collecting the images at the left waypoint, continued to the central one, and finalised at the right waypoint. In the case that it was a 2-lateral waypoint, the UAV started with the left-central-right tour, rotated 180 degrees, and continued with the left-central-right waypoints of the other lateral since when it rotated, it was located at the left waypoint of the other side of the canopy, as indicated in Figure 5.7.

Since ACO-MMAS is a stochastic approach, each time the algorithm is run, the final aerial mission planning generated could differ from the previous one. Therefore, the algorithm was run several times for each of the nine scenarios presented in Table 5.1 in order to account for the variability and be able to compare the results within the same scenario, and the one which presented the least UAV path, or the least UAV turns, or least crossing between UAV paths is displayed. Thus, in order to illustrate the results of this algorithm with all the scenarios, they were represented in the form of boxplots to be able to visualise the variableness. Figure 5.11 compares the path length using the ACO-MMAS algorithm for the two vineyards (B9 and B7). Figure 5.11a made the comparison based on the forbidden-area difficulty level (low, medium, and high), whereas Figure 5.11b used the number of UAVs as the comparison baseline. The path length was shorter for vineyard B7 than for B9 for the low and medium cases of difficulty. However, the variability of vineyard B7 was higher in all cases except for the medium level of difficulty. As observed, the path length was always shorter with the low level of difficulty, and it increased with the rise of difficulty. The same happened with the number of UAVs; the length was shorter in the case of a single UAV, and it grew with the addition of more platforms. Regarding the number of UAVs, vineyard B7 tended to produce shorter path lengths compared to vineyard B9, but the variability it included was higher for the cases of two and three UAVs.

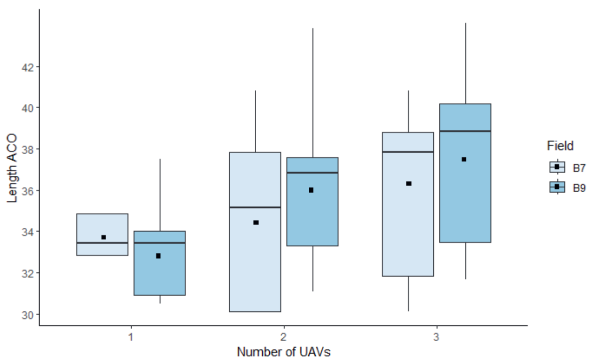
Table 5.1. Aerial mission planning generated using the ACO-MMAS algorithm for the three different densities, considering single and multiple platforms. The green dot indicates the starting position and the red dot is the end location. The blank areas, which are not included in the trajectory, are the forbidden areas introduced to the algorithm.

	1 UAV	2 UAVs	3 UAVs
Low density			
Medium density			





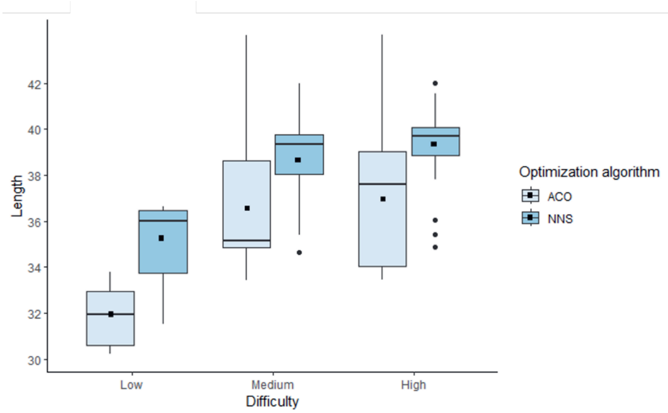
(a)



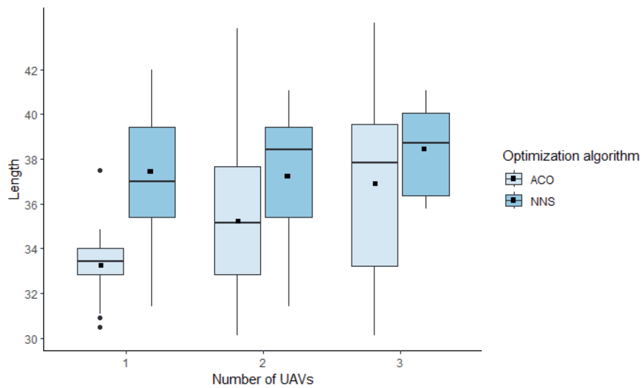
(b)

Figure 5.11. Boxplots comparing path lengths from the two vineyards (B9 and B7), based on the ACO-MMAS algorithm. The y-axis represents the length of the optimised path. The horizontal black line represents the median value, while the black square depicts the average. (a) The comparison is made with the level of difficulty, which is based on the number of forbidden areas. (b) The number of UAVs is implemented to perform the comparison.

The comparison between the path length computed with ACO-MMAS and NNS algorithms, the latter being used as a reference, is presented in Figure 5.12. Again, the path length when using the low-difficulty algorithm is shorter compared to the medium and high difficulty. Also, the variability of the ACO-MMAS algorithm is narrower at low difficulty compared to the same algorithm but with increasing difficulty. Nevertheless, the width of the NNS boxplots is narrower than that of ACO-MMAS for the two most challenging scenarios. On the other hand, the boxplots regarding NNS in Figure 5.12b were kept constant, along with the increasing number of UAVs. There was a big difference in path length between ACO-MMAS and NNS using one UAV, but the difference decreased when more platforms were considered. Overall, the path length computed with ACO-MMAS was always shorter than for NNS, with a difference of length ranging from 2.4% to 24.2% longer for NNS than for ACO-MMAS. Regarding the elapsed time, it ranged from 30.7 to 119.8 seconds, with an average of 49.6 seconds, just above two minutes of average running time. This short elapsed time allows for obtaining results almost in real time, as well as the performance of the second flight, to get to know the state of the vineyard.



(a)



(b)

Figure 5.12. Boxplots comparing the length derived from both optimisation algorithms. The horizontal black line indicates the median value, and the black square indicates the mean number. (a) The grade of difficulty is considered. (b) Including the number of UAVs.

5.4 Discussion

5.4.1 Novelty of the study

The framework proposed in this project optimises the route that the UAVs need to follow in order to enhance data collection for object detection purposes in vineyards. The input requires data from the biophysical environment captured during a survey flight, which integrates the Digital Terrain Model and the Digital Surface Model to compute the Canopy Height Model. The CHM allows the identification of the areas of interest, which are then considered waypoints, and the areas without agronomic interest or areas with hazards for the UAV, which are designated as forbidden areas. Moreover, the information obtained during the survey flight provides insights into the status of the vegetation, for instance, the number of missing plants within the field, which is relevant for the winegrower for decision-making regarding replanting the areas with more missing plants. Furthermore, the optimised data collection empowers the obtention of valuable data from the whole grape bunch, which boosts the calculation of its size and other phenotypic traits (Ariza-Sentís et al., 2023a) related to yield estimation.

This study validated the proposed method in two vineyards with different slope conditions, and data was collected at two different seasonal moments (harvesting in 2021 and veraison in 2022). Also, the UAV mission height of the survey flight differed in each flight: 30 meters in 2021 and 20 meters in 2022. Further, each vineyard included three regions with an increasing number of forbidden areas, ranging from 8% to 22% of restricted areas compared to the total area covered. Also, we have chosen to focus on the vertical trellis system due to its prevalence in Spain, a leading wine producer, and the location of our study. In Spain, 45.1% (430,039 ha) of the total vine area for processing (952,829 ha) employs the trellis training system, with several regions exceeding 50% and some reaching up to 78%, as per official data from the Spanish Ministry of Agriculture (source: https://www.mapa.gob.es/es/estadistica/temas/estadisticas-agrarias/vinedo 2019_tcm30-562250.pdf, page 16). Additionally, the shift towards trellised vineyards is noteworthy due to its ability to reduce harvesting costs and increase vine productivity (source: https://doi.org/10.1016/j.agee.2021.107448). The experiment was designed as such, aiming to boost the robustness of the method and analyse its applicability with increasing levels of difficulty.

5.4.2 Advantages of the study

The method proposed in this study was able to optimise the path length in all cases compared to the base algorithm (NNS), with the potential to reduce the path length up to 24.2%, which allows better usage of the UAV batteries and being able to cover a greater area of land, addressing two major limitations of path planning (Aggarwal and Kumar, 2020; Oksanen and Visala, 2009). Furthermore, to the best of our knowledge, there is a lack of UAV path planning designed for agricultural purposes to map the sides of the canopy, as is the case for crops trained on vertical trellis. Therefore, the considerations and framework described in this research study can create a framework for future projects, which can implement and train other tailor-made algorithms for optimal acquisition of images for fruit detection purposes and compare the metrics obtained in terms of path length and elapsed time compared to our ACO-MMAS algorithm and other algorithms that do not include optimisation, as is the case of Nearest Neighbour Search.

A significant advantage of this method is its reliance solely on RGB channels for exploratory analysis, unlike other studies that use additional bands, such as the near-infrared for NDVI calculations (Karatzinis et al., 2020). Vegetation indices can sometimes yield inaccurate segmentations due to factors like cover crops or mixed pixel effects (Vélez et al., 2020). Given the presence of cover crops in the vineyards of this study, the method employed photogrammetry and RGB images to determine the CHM, offering a more accurate and cost-effective alternative for farm managers.

Finally, the experience gained in designing a UAV path planning with ACO-MMAS has been shared with the community by making the algorithm open-source (Valente et al., 2023).

5.4.3 Limitations and future work

One limitation of the presented work is the overlap between continuous images taken by the UAV, for example, in Figure 5.6. This percentage can be computed by applying trigonometric formulas and considering the different angles present. In this way, considering that the Field of View (FOV) of the ALTUM-PT camera is 48°, the camera is tilted 37.5°, the UAV records at 2.3 m height, and, for vineyards B9 and B7, the horizontal dimensions of the grid are 2.05 meters and 2.1 meters, respectively, the calculation for the B9 vineyard would be the hypotenuse of the triangle created between the tilted angle and the UAV height, which is 3.78 meters, and considering the FOV, each image will horizontally capture 3.36 meters. Hence, by calculating the difference between the 2.05 meters and the 3.36 meters, it can be concluded that each image will contain a 38% overlap with respect to its adjacent image. Nonetheless, since the purpose of the study is to detect grape bunches in the vineyard and not to count the number of grape bunches present in each row, this overlap was dismissed in this study. For future studies, this overlap percentage will be considered in order to improve the workflow and adapt it for fruit counting in hedge row systems.

The quality and accuracy of the data collected on grape bunches using UAVs are significantly influenced by the camera tilt, the platform rotation, and the grid dimensions selected for the aerial survey. Adjusting the camera tilt and the platform rotation allows for images to be captured from multiple angles, mitigating the issue of leaf occlusion by providing varied perspectives of the grape bunches. This is critical for ensuring that the fruits are fully visible and can be accurately detected and tracked. Moreover, the selection of grid dimensions determines the region of interest of each image and, thus, the overall coverage of the vineyard. Consequently, it is of crucial importance to determine the size of the grid by using information on the biophysical environment of the vineyard ("2.2.2. Determination of the field grid and waypoints").

Further, in order to validate the potential of this study, future work should focus on performing object detection for grape bunch identification using the proposed methodology and check if tailor-made path planning could improve object detection. Also, all the processes mentioned in this study regarding the survey flight can easily be automatised to obtain the orthomosaic, CHM, and zonal statistics (Ariza-Sentís et al., 2023c). However, as already mentioned, the ACO-MMAS algorithm was automatised using MATLAB software. Moreover, this method was initially developed to acquire side images for optimal object detection and tracking in agricultural fields with vineyards. Nevertheless, the rationale behind the development of this tool can be applied for optimal and precise pesticide spraying and fertiliser application, among other agricultural tasks, as has already been studied in experimental conditions (Faiçal et al., 2017). Finally, since woody crops trained in vertical trellis have a similar crop structure to the vineyards used in this study, future work should focus on extrapolating the gained knowledge to other crops trained with similar characteristics, for instance, apple orchards.

5.5 Conclusions

The presented ACO algorithm generates a UAV path planning specifically designed to optimise object detection purposes in woody crop environments, considering the biophysical characteristics of the field. It computed optimised paths in two different vineyards presenting leaf occlusion and with three levels of difficulty regarding the number of areas above which the UAV could not fly. Moreover, the algorithm included the option of utilising a single or multiple UAVs simultaneously. The method prioritises image acquisition, especially when fruits are partially hidden, by capturing the target from multiple angles, inclusive of frontal views. All the optimised routes, which were computed using ACO-MMAS, were compared to the Nearest Neighbour Search (NNS) algorithm, and in all cases, ACO-MMAS could generate shorter paths with respect to NNS, reaching a maximum difference in length between algorithms of 24.2%. Future endeavours should focus on validating whether tailor-made path planning can improve object detection metrics.

Chapter 6

Experimental implementation of UAV path planning for improved grape bunch detection

This chapter is based on:

Ariza-Sentís, M., Baja, H, Vélez, S., van Essen, R., Valente, J., 2024. Comparative Analysis of Single-Angle and Multiple-Angle Data Collection Strategies for Detecting Partially-Occluded Grape Bunches: Field Trials. Journal of Agriculture and Food Research [under review]

Abstract

Extracting phenotypic traits of grape bunch is crucial for accurately monitoring grape quality, health, and yield estimation. This is important for optimising resources, enhancing marketing strategies, and boosting overall agricultural productivity. While most research concentrates on data processing algorithms, this study focused on the preceding step: collecting reliable data. Object detection and tracking enable precise monitoring and quantification of fruit, facilitating agricultural management. This study compares two data acquisition methodologies for grape bunch detection and tracking in a commercial vineyard where leaf removal was not performed: a traditional single-angle approach and a multiple-viewing angle method designed to mitigate fruit occlusion issues. The PointTrack algorithm, trained and validated using MOTS annotations, was employed to evaluate detection and tracking performance through metrics of three trials. The multiple-angle method achieved i) an improved detection accuracy of 74% compared to 23% for the single-angle approach and ii) enhanced tracking metrics, with the multiple viewing angles trials metrics ranging from -1.35 to 3.84 for sMOTSA and MOTSA, and iii) higher correlation and lower RMSE of grape bunch phenotypic traits (OIV codes 202 and 203) compared to ground truth measurements (R^2 = 0.53, RMSE = 19.13). Nonetheless, the multi-angle technique was compromised by motion blur due to UAV movements, complicating the tracking process. This study underscores the importance of strategic data acquisition in improving object detection and tracking performance for fruit detection and tracking. Future work should extend this methodology to other fruit varieties and environments to validate its broader applicability, enhancing the reliability of yield estimation in precision agriculture.

6.1 Introduction

DL has been applied in recent years in the agricultural domain, for instance, in fruit detection and tracking (Koirala et al., 2019; Naranjo-Torres et al., 2020), witnessing notable advancements and offering promising research lines for yield prediction (Ariza-Sentís et al., 2023b; Chen et al., 2019; Wenli Zhang et al., 2022c) and fruit growth monitoring (Aguiar et al., 2021; Fukuda et al., 2021), among others. Within DL, CNNs have proven to be particularly effective since they learn complex features from images and videos, which allow accurate fruit recognition in complex field environments, such as challenging illumination conditions (Kang and Chen, 2020). These technologies offer great potential in the agricultural sector for fruit counting, phenotyping, and consequent yield prediction, abating inspection time and reducing labour costs.

One of the advantages of DL is domain adaptation (Hsu et al., 2020; Zheng et al., 2020), which consists of applying the knowledge gained in one specific field to another domain. For instance, (Dias et al., 2018) developed a fruit flower detection for multiple species trained on apple flower images, and tested on apple, peach, and pear flowers. Further, (Wan and Goudos, 2020) implemented Faster R-CNN for multi-class fruit detection, including apple, mango, and orange labels, which benefits from a common characteristic between those fruits: their circularity.

Despite the potential of DL in fruit counting (Ferrer-Ferrer et al., 2023), challenges can lead to under or overestimation, for instance, occlusion (Lu et al., 2018; Mirbod et al., 2023). Occlusion occurs when fruits are partially or fully hidden, typically by leaves and branches, complicating the detection and tracking task (Íñiguez et al., 2021). Fully hidden fruits, enclosed by leaves, are not detectable from any angle, whereas partially obscured fruits can be seen better from specific angles. (Liang et al., 2024) proposed adding spherical shapes prior to detection, while (T. Li et al., 2022) suggested a 3D fruit localisation method that determines centroid coordinates and approximates shape. However, these solutions were only tested on spherical fruits, which does not apply to grape bunches. (J. Chen et al., 2021) proposed a method to detect ripe fruits by removing the complex background of colourful ripe fruits. However, this method is not effective when applied to grape bunches at an early stage of development or for white varieties.

Furthermore, detection and tracking metrics suffer from fruit occlusion. Several authors have focused on solving this reduction in metrics, but focusing their research on post-processing techniques to reach it (Abbaspour and Masnadi-Shirazi, 2022; Boogaard et al., 2020; Feng et al., 2022). Nevertheless, the focus can also point to the optimal acquisition of the datasets by considering the specific knowledge domain for which they are being acquired (Ariza-Sentís et al., 2024b). Therefore, while most research targets data processing algorithms (J. Chen et al., 2021; T. Li et al., 2022), this study targets the initial step of gathering accurate data. To detect partially occluded fruits, (Ariza-Sentís et al., 2024a) proposed a method that acquires images or videos from the side of the canopy, considering multiple viewing angles (frontal, from the left side, and the right side) to increase the chance of observing the fruit at its full size.

Following their rationale, this study aims to validate in a commercial vineyard with leaf occlusion the proposed framework and compare the obtained results with a traditional single-angle methodology for acquiring the data. The results are presented as a comparison between the grape bunch detection and tracking metrics, fruit counting, and correlation with ground truth (GT) measurements obtained without considering how the data is acquired and the results achieved by actively thinking about the most optimal acquisition that considers multiple viewing angles.

6.2 Materials and Methods

The research process that was carried out is outlined in Figure 6.1, illustrating the employed workflow. The focus of attention was driven already to the first step: data acquisition. Two different methodologies were employed to gather the necessary data. The first method implemented a multi-angle viewing approach, which involves collecting data from various perspectives to reduce errors in fruit detection caused by leaves and branches blocking the view. It was designed specifically for woody crop environments, taking into account the biophysical characteristics of the field. For further details on the method, refer to (Ariza-Sentís et al., 2024a). This approach was adopted to test the hypothesis that it is more effective for object detection and tracking, while also addressing issues of occlusion. The second used the traditional method that consisted of flying the UAV to record the side of the canopy without considering any enhancement, similar to (Ariza-Sentís et al., 2023d). The following steps, in white, were common for both methodologies and were composed of data cleaning, annotation of the grape bunches, and training/validating the PointTrack (Xu et al., 2020) algorithm. The workflow was finalised with the comparison in metrics, fruit counting, and correlation with ground truth measurements for phenotyping obtained with each procedure.

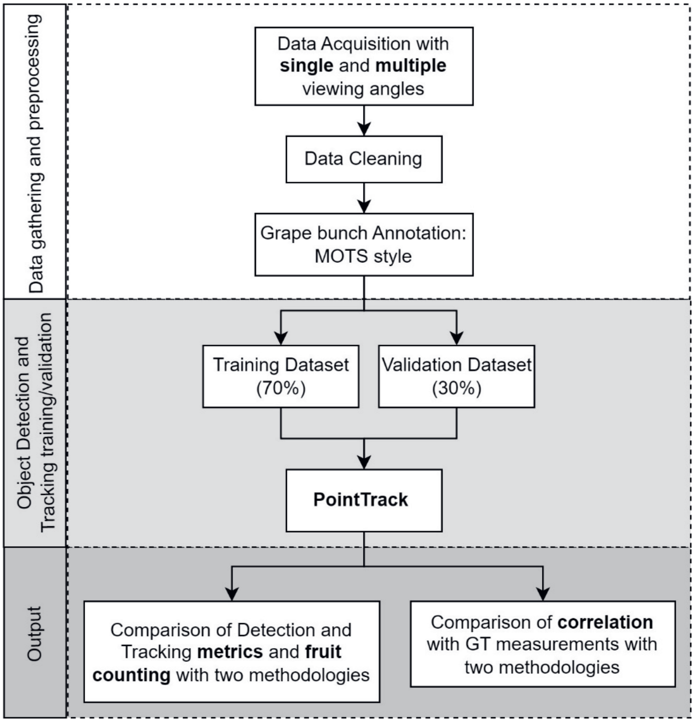


Figure 6.1. Flowchart of this research. Data gathering was performed using two methodologies: single-angle without any enhancement, and multiple-angle to avoid occlusion. The next step was to carry out data cleaning and data annotation with the MOTS style, followed by training and validating the object detection and tracking algorithm. Finally, a comparison of metrics, fruit counting, and correlation with GT measurements was executed between both methodologies.

All the information regarding the description of the data acquisition process is summarised in Table 6.1.

Table 6.1. Data acquisition specifications.

How the data were acquired	UAV: DJI Phantom4 RTK (integrated sensor). Sensor characteristics: focal aperture range of f2.8 - f.11, shutter speed of 8-1/8000 s <u>Flight details</u>: Flight speed: not stable, between 0.1 and 1 m/s. Flight altitude: 3 m above ground level (AGL).

	Video specifications: Videos PathPlanning_1 and PathPlanning_3 have a frame width of 1920, a frame height of 1080, and a frame rate of 30.00 frames/second. The remaining videos share the following characteristics: frame width of 3840, frame height of 2160, and 29.97 frames/second as frame rate. Videos NoPathPlanning_2 and NoPathPlanning_3 have the same frame width and height, but a frame rate of 30.00 frames/second. A total of 11 videos and their grape bunch annotations are provided. These include frames from both sides of the canopy of the vineyard rows, each having a length of approximately 110 meters. Furthermore, videos NoPathPlanning_2 and NoPathPlanning_3 also include vineyard trunks and pole labels.
Description of data collection	Video Composition: eight videos (named PathPlanning_*) provide a multiple-angle view, each from a different vine plant. The other three videos (named NoPathPlanning_*) offer a frontal view of the canopy's side. These record the same plants as those with multiple perspectives, allowing for comparison. Recording details: the videos were captured between September 19 and September 20, 2023, during the harvesting period. Both days had sunny conditions and a wind speed below 0.5 m/s. Annotation Information: all the videos have been annotated using CVAT software, employing the MOTS annotation style.
Data source location	Institution: Wageningen University & Research City/Town/Region: Tomiño, Pontevedra, Galicia Country: Spain Latitude and longitude (and GPS coordinates) for collected samples/data: 41°57′18.5″N 8°47′41.2″W

6.2.1 PointTrack implementation and metrics

The implementation of the PointTrack algorithm in this study was largely similar to that in Ariza-Sentís et al. (2023a), except for image resolution differences due to the utilisation of different sensors. Transfer learning (Torrey and Shavlik, 2010) was employed to train the Spatial Embeddings (SE) model. An Adam optimiser (Kingma and Ba, 2017) with a learning rate of 5×10^{-5} and a finetuning rate of 5×10^{-6} was used. The SE model (Neven et al., 2019) was trained with a batch size of 20 and 1200 epochs. Hyperparameters were optimised by adjusting their values up and down until there was no further improvement in performance or overfitting was detected. During SE training, image crops were vertically oriented to match the grape bunches' shape, with resolutions of 256 x 512 and 512 x 1024 pixels for initial training and finetuning, respectively. The PointTrack tracking component was trained with a batch size of 32 and 100 epochs.

To compare the two proposed methodologies and determine which was the most valid method for object detection and tracking in vineyards without leaf removal, several metrics were computed to assess their ability to detect and track grape bunches. Two detection performance metrics, MOTSP (Multiple Object Tracking and Segmentation Precision) and MODSP (Multiple Object Detection and Segmentation Precision) were calculated using Equations 1 and 2. Additionally, MOTSA and sMOTSA were obtained as detection metrics by applying Equations 3 and 4.

$$MOTSP = \frac{\tilde{T}P}{|TP|} \tag{1}$$

$$MODSA = \frac{TP}{|TP|} \tag{2}$$

$$MOTSA = \frac{|TP| - |FP| - |IDS|}{|M|} \tag{3}$$

$$sMOTSA = \frac{\tilde{T}P - |FP| - |IDS|}{|M|} \tag{4}$$

Where TP are true positives, which represent the number of masks that were properly detected compared to the ground truth masks, with an IoU value over 0.5; T̃P are soft true positives, which consists of the sum of IoU for all the TP; FP are false positives, which represent the number of masks identified as grape bunches when they actually were not;

IDs which consist on the number of masks that switched ID compared to the previous frame in which they appeared; and M stands for the number of GT masks.

Lastly, a comparison regarding the total count of grape bunches per video between the two methods and the real value obtained from the annotations was calculated, along with a correlation with ground truth measurements for phenotypic purposes.

6.3 Results

A series of experiments were conducted to evaluate the performance of the algorithm. The most effective trials were as follows:

- Trial 1: training the algorithm exclusively with multiple viewing angle data
- Trial 2: training the algorithm exclusively with single-viewing data
- Trial 3: training the algorithm with a combination of multiple and single viewing angle data

6.3.1 Detection and Tracking metrics

Table 6.2 presents the detection and tracking metrics for each trial. The video number remained consistent across trials. Some values are negative due to the occurrence of false positives. It was observed that for the single-angle dataset, Trial 2 achieved the highest detection and tracking metrics (sMOTSA, MOTSA and MODSA equal to -0.08), while for the multiple-angle dataset, Trial 3 exhibited the highest metrics (positive values for all sMOTSA, MOTSA and MODSA). This can be attributed to the fact that Trial 2 included only single-angle data, allowing the algorithm to learn the patterns of that specific dataset effectively. In contrast, Trial 3, which incorporated both multiple and single viewing angle data, enabled the algorithm to generalise better for the multiple-angle scenario.

Table 6.2. Grape bunch detection and tracking metrics (sMOTSA, MOTSA, MODSA, AND MODSP) of the three executed trials.

TRIAL 1								
Video	Category	sMOTSA	MOTSA	MODSA	MODSP	Ground Truth	Tracked	Tracked/Ground Truth
1	Single angle	-1.18	-1.18	-1.18	100	45	10	22%
2	Single angle	-0.08	-0.08	-0.08	100	87	3	3%
3	Multiple angles	-16.21	-12.92	-11.08	64.18	51	23	45%

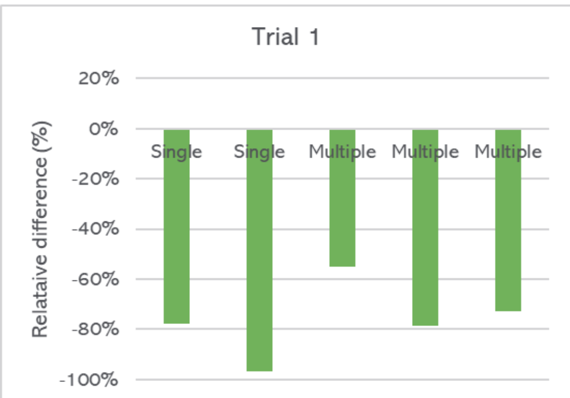
4	Multiple angles	-4.14	-3.76	-3.61	90.26	65	14	22%
5	Multiple angles	-2.62	-0.76	-0.28	71.17	77	21	27%

TRIAL 2								
Video	Category	sMOTSA	MOTSA	MODSA	MODSP	Ground Truth	Tracked	Tracked/Ground Truth
1	Single angle	-1.18	-1.18	-1.18	100	45	10	22%
2	Single angle	-0.08	-0.08	-0.08	100	87	3	3%
3	Multiple angles	-5.74	-5.5	-5.42	92.74	51	59	116%
4	Multiple angles	-2.06	-1.53	-1.42	85.5	65	32	49%
5	Multiple angles	-2.2	-0.8	-0.44	71.16	77	45	58%

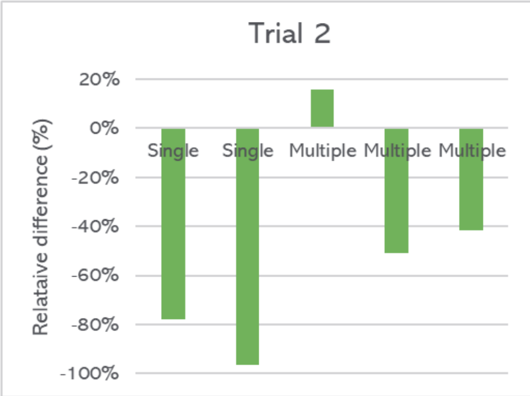
TRIAL 3								
Video	Category	sMOTSA	MOTSA	MODSA	MODSP	Ground Truth	Tracked	Tracked/Ground Truth
1	Single angle	-7.51	-5.44	-4.98	67.92	45	10	22%
2	Single angle	-0.9	-0.48	-0.46	93.16	87	21	24%
3	Multiple angles	-7.08	-4.7	-4.14	65.93	51	21	41%
4	Multiple angles	-1.35	0.3	0.68	75.85	65	13	20%
5	Multiple angles	0.69	3.44	3.84	70.8	77	15	19%

6.3.2 Grape bunch counting

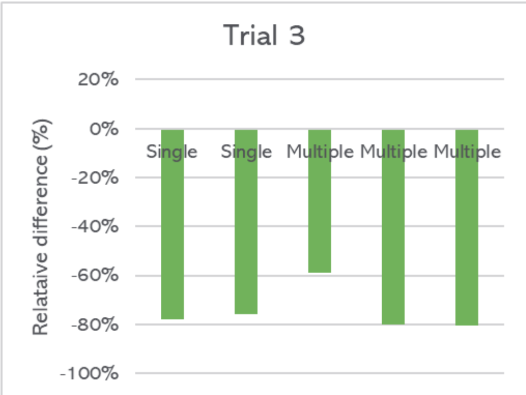
In addition to the detection and tracking metrics, the algorithm's ability to count the number of grape bunches was evaluated. Figure 6.2 shows the relative difference between the ground truth number of grape bunches present in each video and the predicted number. In most cases, the value is negative, indicating undercounting. The closer the value is to 0, the more accurate the detection count. Positive values indicate overcounting of the predicted grape bunches.



(a)



(b)



(c)

Figure 6.2. Relative difference between the actual and predicted number of grape bunches for each trial. The values are negative due to undercounting.

6.3.3 Fruit occlusion

Furthermore, to visually validate the importance of occlusion, several images of the same plant, both with single and multiple viewing angles, are presented in Table 6.3. It can be observed that, although the detection and tracking metrics of the three trials in Table 6.2 are lower for multiple-angle compared to single-angle, incorporating multiple points of view reduces the occlusion of grape bunches, making them easier to detect and track.

Table 6.3. Comparison of the same plant seen with a single viewing angle (with occlusion) and multiple viewing angles (without occlusion) dataset. The red circles indicate the location of the occluded grape bunches which are not visible with the single viewing angle.

Single viewing angle (occlusion)	Multiple viewing angles (no occlusion)
	
	
	

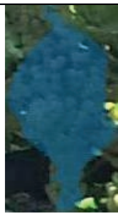
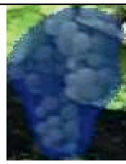
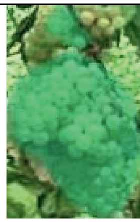
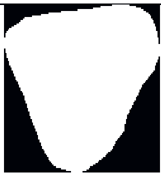
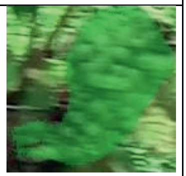
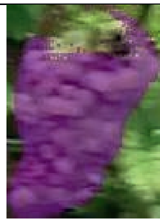
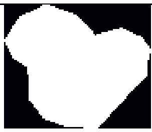
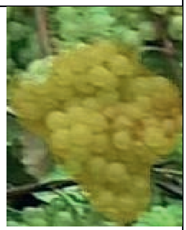
6.3.4 Phenotypic assessment

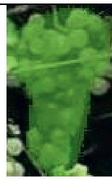
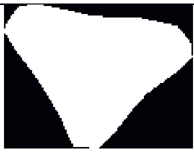
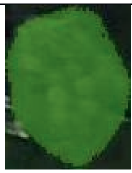
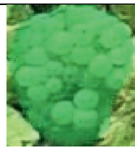
The OIV (International Organisation of Vine and Wine, 2009) has established several standards for characterising the phenotyping of grape bunches. For example, bunch length and width correspond to the descriptor codes OIV 202 and 203, respectively. According to the OIV guidelines, a sample size of 10 bunches is required to determine these descriptors. Therefore, in this study, 10 bunches were analysed to compare the phenotyping traits (grape bunch length and width) between annotated and detected bunches. Measuring these descriptors is crucial for gaining insights into the physical dimensions of the bunches, which serve as indicators of fruit quality and vine health (Kandilli et al., 2022). Moreover, the size of grape bunches is directly related to the harvest yield, thus enabling more precise yield estimations (Palacios et al., 2023).

Table 6.4 displays the annotated and detected masks of 10 grape bunches for both single-angle and multiple-angle perspectives. It can be observed that the sizes and shapes differ between single and multiple angles, even for the same grape bunch GT, due to fruit occlusion, as highlighted in Table 6.3, which plays a critical role in hiding full shapes. In addition, grape bunches appear more accurately shaped in the multiple-angle masks since they are completely visible from at least one of the three angles. When the grape bunch is fully observed from all three views, the best one, which is less blurred, with a lower percentage of occlusion, and with a better contrast with the surrounding canopy, is selected for extracting their phenotypic traits.

Table 6.4. Grape bunch annotations (second and fourth columns) and bunch mask detections obtained with PointTrack (third and fifth columns). The shapes of the same grape bunch number differ from a single and multiple-angle viewing due to occlusion.

Grape bunch number	GT single-angle	Single-angle detection	GT multiple-angle	Multiple-angle detection
1				
2				

3				
4				
5				
6				
7				
8				

9				
10				

Further, Figure 6.3 compares the ground truth measurements of each bunch's dimensions (length and width, in pixels) and the predicted measurements obtained from single and multiple perspectives. It can be observed that the methodology proposed had a higher correlation and lower RMSE (R^2 = 0.53, RMSE = 19.13) compared to single-angle (R^2 = 0.39, RMSE = 28.05).

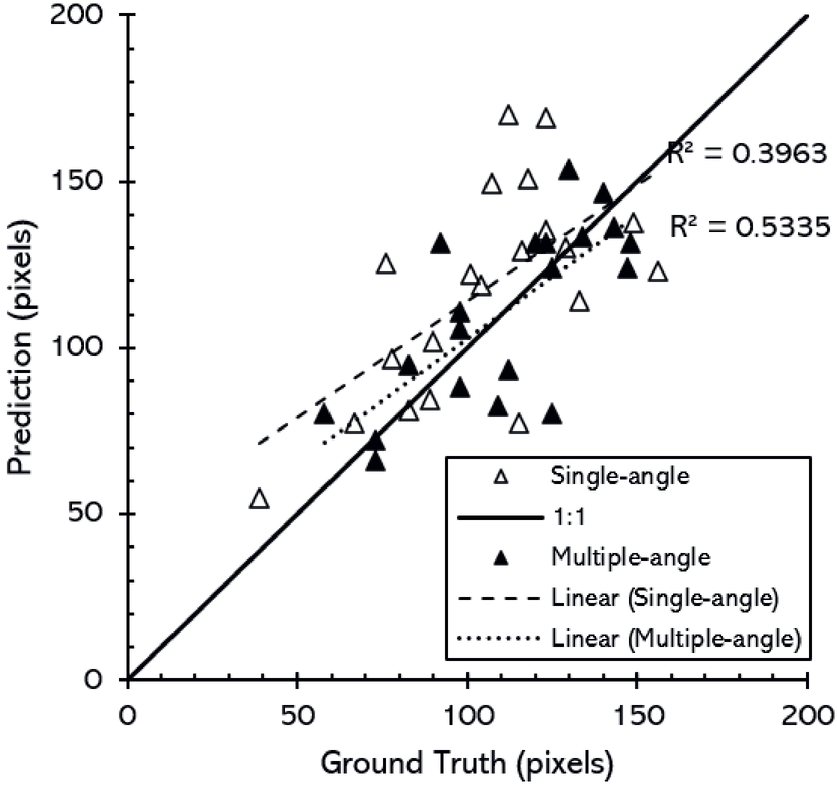


Figure 6.3. Correlation between the ground truth measurements of the grape bunch dimensions (OIV 202:length and OIV 203:width, in pixels) and the predicted measurements using single-angle and multiple-angle methodologies.

6.4 Discussion

Fruit occlusion presents a significant challenge in object detection and tracking (Gongal et al., 2016; Kestur et al., 2019; Lu et al., 2018). To address this issue, a multiple-angle method was implemented, capturing images from various viewpoints to reduce occlusion and enhance visibility. The detection and tracking metrics obtained were low due to several limitations, such as false positives caused by colour similarities and varying illumination conditions (Bargoti and Underwood, 2017a; Chen et al., 2017), which were expected based on the findings presented in Chapter 4 (Ariza-Sentís et al., 2023a). Despite these challenges, the multiple-angle approach demonstrated a more accurate count of grape bunches compared to single-angle methods. Figure 6.2 showed that the relative difference between the actual and predicted number of grape bunches was more accurate with multiple angles, despite significant undercounting in most cases. The average ratio between Tracked and GT values for single viewing angles ranged from 13% to 23%, while multiple angles consistently outperformed, ranging from 27% to 74%, with the highest metrics observed in the second trial (Table 6.2).

Illumination conditions varied across trials, necessitating validation to ensure shadows did not significantly impact detection limitations. Table 6.4 remarks on the shape differences between single-angle and multiple-angle detections, with the latter providing a more realistic representation of grape bunches. Figure 6.3 further supported the effectiveness of the multiple-angle method, showing increased correlation with ground truth measurements from an R^2 of 0.39 with single-angle to 0.53 with multiple-angle, and a reduction in RMSE from 28.05 to 19.13. However, tracking using three angles presented difficulties due to motion blur from UAV movement, causing the camera to lose track of the fruit, and impacting the continuity of ID numbers through frames. This issue was particularly evident in grape bunches 5, 6, and 7.

Despite these challenges, the improvement achieved by including multiple viewing angles over a single viewing angle emphasises the importance of a well-structured data acquisition plan. Proper planning can significantly enhance the accuracy of fruit detection, even under non-ideal conditions. This study demonstrates that multiple viewing angles are a valuable strategy for improving the detection and counting of partially occluded fruit, which is essential for several operations such as accurate phenotyping, reliable yield estimation or disease detection. Future work should implement the same methodology in red varieties and other fruit species to confirm the obtained results.

6.5 Conclusions

This study demonstrates that employing multiple perspectives for fruit detection and counting is more effective than relying on a single perspective, as it minimises occlusion and enhances the robustness of the algorithm. In addition, it highlights the significance of strategic data acquisition in improving DL models for object detection and tracking. The PointTrack algorithm was utilised to gather detection and tracking metrics, along with assessing phenotypic traits in grape dimensions (OIV codes 202 and 203), which were then compared to ground truth values. Using a multi-angle approach significantly reduced occlusion, enhancing the visibility and counting accuracy of grape bunches compared to conventional single-angle methods, leading to more precise phenotyping and, consequently, better yield predictions. The multi-view approach achieved an accuracy of 74%, while the single-angle method only identified 23% of the present grape bunches. Moreover, incorporating multiple perspectives improved the correlation with ground truth measurements, increasing the R^2 from 0.39 with a single angle to 0.53 with multiple angles, and reducing the RMSE from 28.05 to 19.13. Future research should expand this methodology to other types of fruit and settings to confirm its wider applicability.

Data access

All data collected for this chapter were carefully annotated, post-processed, and uploaded open access to Zenodo. A detailed scientific manuscript was published. This allows other researchers to reproduce the experiment and conduct their own experiments using the collected data.

Ariza-Sentís, M., Wang, K., Cao, Z., Vélez, S., Valente, J., 2024. GrapeMOTS: UAV vineyard dataset with MOTS grape bunch annotations recorded from multiple perspectives for enhanced object detection and tracking. Data Brief 54, 110432. https://doi.org/10.1016/j.dib.2024.110432

Chapter 7

Synthesis

7.1 Review of Research Questions

The main objective of this thesis was to establish a framework aimed at enhancing data collection in order to boost object detection and tracking in PF to improve agricultural operations such as disease assessment for precision spraying and phenotyping for yield forecasting, considering the field environment and avoiding fruit occlusion. This goal was divided into four research questions.

1. **What are the current status and challenges of integrating object detection and tracking in precision farming?** *Chapter 2* provided a systematic review of advancements in object detection and tracking within the field of PF. Successful cases, divided into categories, were examined in detail, along with a section addressing their issues. Furthermore, a list of directions for future research was provided, with a clear emphasis on the need to provide open-source datasets and to develop strategies to enhance data collection in the agricultural context.

2. **How can a two-phase framework be used to monitor and manage vertical-trellis crops efficiently?** In *Chapter 3*, a disease factor assessment analysis was developed and automated to assess the presence of *Botrytis cinerea* using a two-phase framework. This method included an initial general monitoring of the environment of the field while mapping the disease from above, followed by a closer assessment that incorporated an optimised path planning to get insights on the health status and dimensions of grape bunches, useful for spraying and phenotyping, among others. Moreover, the economic, energetic, and sustainable aspects of the method were compared across three platforms: UAV, UGV, and tractor.

3. **How can fruit occlusion be mitigated, and what is the effectiveness of including multi-angle perspectives?** Following the rationale of *Chapter 2*, which emphasised the importance of data collection, *Chapter 4* implemented an object detection and tracking algorithm (PointTrack) for grape bunch and berry phenotyping without enhanced data collection. This approach resulted in low detection metrics due to fruit occlusion. Consequently, *Chapter 5* developed a method that combined the approach of *Chapter 4* with a multi-angle perspective to mitigate fruit occlusion.

4. **How does the proposed framework compare to a single-angle method?** *Chapter 6* implemented the framework established in *Chapter 5* in a commercial vineyard to compare the effectiveness of a multiple-view versus a single-view strategy. It included a comparison of bunch detection and tracking metrics, fruit counting, and correlation of phenotypic traits, which is relevant for yield prediction and to assess diseases.

The remainder of *Chapter 7* is organised as follows: *Section 7.2* summarises the key findings and the contributions to the scientific community; *Section 7.3* reviews the societal and environmental benefits of this study; *Section 7.4* explores the limitations and future outlook; and *Section 7.5* provides a summary of conclusions.

7.2 Main Findings and Scientific Contributions

This thesis serves as a groundwork for shifting focus towards data collection by addressing the questions: *What* data should be acquired? and, *How* should the data be collected? The four research questions were designed to tackle these findings, making relevant scientific contributions.

7.2.1 Importance of data collection

Current research focuses solely on object detection and tracking metrics (Abbaspour and Masnadi-Shirazi, 2022; Boogaard et al., 2020; Feng et al., 2022), without considering the prior step which can already increase accuracy and performance. While AI offers domain adaptation (Talukdar et al., 2018; Torrey and Shavlik, 2010), it is less effective in agriculture without recognising that plants are living entities with dynamic growth, requiring tailored solutions (Pezzementi et al., 2018). Therefore, it is crucial to consider the purpose of data acquisition and implement data collection methods that align with this objective.

In the context of extracting phenotypic traits to evaluate the sanitary condition of grape bunches and berries (Mutka and Bart, 2015; Zheng et al., 2022) or to predict yield based on their dimensions, the data collection process is crucial. Early phenotyping provides farmers with insights into the health of grapevines, enabling early phytosanitary applications which prevent yield loss (Song et al., 2021). Understanding grape bunch dimensions months before harvest allows for informed decision-making (Kuska and Mahlein, 2018). Grape bunches need to be viewed from a similar height and from multiple perspectives to capture their full shape and extract OIV descriptors (International Organisation of Vine and Wine, 2009) such as length and width (OIV 202 and 203, respectively). Hence, a closer-view flight should be undertaken to ensure complete visibility of the grape bunches, unobstructed by leaves.

The detection of plant diseases presents unique challenges depending on the nature of the disease. For instance, the detection of fungal diseases, like powdery and downy mildew in vineyards (*Uncinula necator* and *Plasmopara viticola,* respectively), which affects the leaves, can be performed using vegetation indices (Acosta et al., 2024; Knauer et al., 2017; Lacotte et al., 2022; Oberti et al., 2014; Pithan et al., 2021). In contrast, *Botrytis cinerea* affects the inner part of grape bunches, being too late to treat once symptoms are visible. Therefore, it is important to assess the risk of disease development based on the disease triangle (pathogen, host, and environment) rather than focusing solely on detection.

Traditionally, Botrytis detection relies on individual instruments (Fedele et al., 2020; González-Domínguez et al., 2015; Hill et al., 2019; Molitor et al., 2016; Reich et al., 2017; Rodríguez-Rajo et al., 2010), such as relative humidity, soil moisture, or temperature sensors placed in limited locations. While these models can reduce phytosanitary treatments by estimating optimal treatment times, they do not account for within-field spatial variability. Often, Botrytis Bunch Rot is treated across the entire field using non-targeted chemical applications as a preventive measure through CPP (Becce et al., 2021; Guo et al., 2021; J. Li et al., 2023; Pham et al., 2020) resulting in blanket treatments.

Chapter 3 introduced a methodology to evaluate the spatial variability of *Botrytis cinerea* development using UAV multispectral imagery in a vineyard (Vélez et al., 2023a). This innovative approach, based on risk assessment, complements existing models to optimise Botrytis detection and phytosanitary treatment application. The methodology calculates the probability of disease occurrence based on biophysical parameters such as areas with higher humidity retention, optimal for fungal development, such as lower DTM and higher LAI due to leaf cover, and identifies these locations as hotspots. The proposed framework targets only plants at risk of disease development by combining risk maps with optimised UAV path planning, developed in *Chapter 5*, to treat only infected plants. This targeted approach has been shown to reduce phytosanitary use by up to 78% (Figure 3.6) and save battery life (Figure 3.7), thus reducing electricity consumption. Consequently, farmers benefit from reduced chemical product costs and produce more environmentally friendly table grapes and wine.

7.2.2 Fruit occlusion

A significant challenge in grape bunch detection is occlusion, common in commercial vineyards where no leaf removal is performed, and only standard management practices are followed. Research in *Chapter 4* employed the PointTrack algorithm (Xu et al., 2020) for grape bunch detection and tracking in a commercial vineyard, revealing low detection and tracking metrics (Table 4.5), mostly due to occlusion and challenging illumination conditions. This highlights the limitations of current algorithms in agricultural environments.

(Nuske et al., 2011) initially suggested that occlusion was not problematic if there were few false positives. However, later studies by the same authors indicated that occlusion is a significant issue in berry detection, as berries cannot be associated with their respective grape bunches (Nuske et al., 2014). (Cossio-Montefinale et al., 2024) noted that fruits on trees such as apples, oranges, and cherries display irregular distributions due to occlusion and irregular growth patterns, whereas plants in structured environments, like tomatoes and strawberries in greenhouses, present less occlusion.

Most research is conducted in experimental vineyards where leaf removal is performed to avoid occlusion (Nuske et al., 2014; Palacios, 2021; Rose et al., 2016; Santos et al., 2020; L. Shen et al., 2023). However, this solution is not economically practical for farmers as it incurs costs without offering any benefits. Therefore, it is vital to develop frameworks applicable to real conditions. *Chapter 5* made a significant contribution by addressing occlusion through the development of multi-view path planning to avoid occlusion (Figure 5.7). To validate this path plan, PointTrack was applied in *Chapter 6* to the same vineyard as in *Chapter 4*, which presents leaf-occlusion. This application aimed to demonstrate the plan's effectiveness and real-world applicability. The results showed that incorporating the multi-angle path plan improved detection accuracy from 23% to 74% (Figure 6.2). Moreover, including multi-angle techniques increased the correlation of phenotypic traits (OIV 202 and 203) from an R^2 of 0.39 to 0.53, and lowered the RMSE from 28.05 to 19.13 (Figure 6.3).

7.2.3 Automation

Automation is essential due to the complexity of data interpretation and the delays between data collection, processing, and decision-making (Pavlovic et al., 2008; Sophocleous, 2021), which can negatively impact grape bunch quality and yield. *Chapter 3* provided an open-source automated framework for disease assessment, covering all steps from raw UAV image extraction to generating disease risk maps and reports that are easy to interpret for researchers and farmers (Figure 3.2) (Ariza-Sentís et al., 2023c). The software, meticulously documented and available open-source, enhances reproducibility. Once validated across different farm conditions, this software can help farmers assess the spatial variability of *Botrytis cinerea* development in their fields.

Automation reduces labour-intensive tasks, such as visual field surveys, and decreases labour expenses and response times, thereby increasing efficiency (Edan et al., 2023). It also improves crop monitoring, enabling timely actions and reducing pesticide use, leading to more sustainable vineyard management (Gackstetter et al., 2023). Figure 3.8 demonstrates that UAVs are more economical for localised infection spraying. Regular field coverage with the BBR software allows for early disease detection and targeted UAV spraying. For early disease assessment and targeted spraying, UAVs are the optimal platform. However, UGVs are competitive when the disease has not been detected at its early stages of developing and there is a widespread infection.

7.2.4 Lack of open-source datasets

Chapter 2 highlighted a significant lack of open-source datasets in the agricultural context (Table 2.3), particularly those with annotations for training object detection and tracking algorithms. During the development of this thesis, three open-source datasets were published (Ariza-Sentís et al., 2024b, 2023e; Vélez et al., 2023b). *Chapter 3* presented a dataset containing raw multispectral images, ground truth points where the *Botrytis cinerea* disease was present, trunk locations, and Ground Control Points for georeferencing purposes. This dataset is valuable for researchers performing digital photogrammetry and 3D reconstruction in precision viticulture. It allows for the study of the effects of different tilt angles on the 3D reconstruction of vineyards and the generation of orthomosaics. It can also be used to develop new vegetation indices and algorithms for disease detection in vineyards and to study the relationship between spectral information and plant health status. The dataset also supports image segmentation and the development of new techniques for trunk detection, plant isolation, and vegetation segmentation. Furthermore, it enables the creation of multispectral dense clouds, providing more information than a single orthomosaic.

Chapters 4 and 6 provided two datasets that include UAV RGB videos along with grape bunch annotations in MOTS (Voigtlaender et al., 2019) annotation style. These datasets addressed the lack of public agricultural datasets and the absence of grape bunch labels in well-known datasets like ImageNET (Deng et al., 2009), PASCAL-VOC (Everingham et al., 2010), KITTI (Geiger et al., 2013), and MS-COCO (Lin et al., 2014). Both datasets contributed to future research in DL for grape bunch detection and tracking. In addition, when annotations are coupled with ground truth information, OIV descriptors (International Organisation of Vine and Wine, 2009) can be extracted, for instance, grape length and width (OIV codes 202 and 203) (Figure 4.4), that serve to characterise a vine variety. Moreover, these descriptors can assist in accurately predicting yield. These datasets are also beneficial for winegrowers and field technicians, providing high-quality videos for visual inspection of bunch monitoring and disease development, eliminating the need for physical presence in the field.

Overall, publishing open-source datasets enables researchers to save time on data collection and Annotation, and eliminates the cost of renting or purchasing the necessary equipment. Consequently, making these datasets publicly available broadens the accessibility of agricultural research. Lastly, publishing the datasets following the FAIR (Findable, Accessible, Interoperable, and Reusable) principles enhances the efficiency and impact of research by promoting better data management and sharing practices.

7.3 Reflection

The technological integration with precision agriculture offers more than just scientific contributions, as mentioned in *Section 7.2*. These technologies must also address the needs and concerns of the broader community, ensuring equitable benefits for both small and large-scale farmers. Reducing chemical use leads to safer and more environmentally friendly products, which benefits the consumers and the farmers. In addition, boosting technological agriculture helps prevent rural depopulation, which brings further advantages to rural areas. By considering these factors, we can promote a more inclusive, sustainable, and effective agriculture, ultimately enhancing food security and environmental health for future generations. Furthermore, it benefits the environment by reducing greenhouse gas (GHG) emissions and improving soil health.

7.3.1 Societal relevance

This thesis holds significant societal relevance, with impacts on both farmers as specific stakeholders and the broader community.

7.3.1.1 Benefits to farmers

Integrating UAVs with object detection and tracking automates time-consuming tasks for farmers, such as conducting detailed field inspections to detect diseases. The framework developed in *Chapter 3* (Figure 3.2) can accurately indicate the affected areas, enabling targeted chemical applications. This approach not only saves time for the farmer's daily work but also diminishes the labour needed for manual inspections (Rahaman et al., 2015). Moreover, these methods optimise the use of resources, including pesticides, water, and fertilisers (Griffin et al., 2018). By applying inputs precisely where and when needed, farmers can reduce costs and boost productivity, fostering more economically sustainable farming practices (Mylonas et al., 2020). In addition, using electric-powered machines reduces the cost per hour for field treatments compared to using tractors, regardless of the disease infection level (Figure 3.8).

Advanced phenotyping technologies, discussed in *Chapters 4 to 6*, enable the monitoring of crop health by detecting deficiencies (Albetis et al., 2017), thereby preventing potential losses and enhancing yields. In addition, phenotyping provides valuable information on the expected yield (Torres-Sánchez et al., 2021), helping farmers to forecast their revenue before the end of the campaign. Lastly, as stated in *Section 3.4*, when UAVs are used instead of UGVs and mostly tractors, there is less soil compaction (Batey, 2009; Nawaz et al., 2013), which promotes better root growth, improved drainage, and reduced soil erosion. These factors also contribute to healthier soils, which at the same time lead to higher yields (Lagnelöv et al., 2020).

The results of *Chapter 3* demonstrate that the proposed framework can reduce chemical use by up to 78% (Figure 3.6). This substantial decrease not only makes the product more sustainable and eco-friendly for grape and wine consumers but also ensures it contains fewer pesticide residues. Moreover, farmers' exposure to synthetics is minimised and consumers also ingest a lower amount of chemicals, which improves long-term health and reduces the risk of associated diseases, such as metabolic and immune disorders, cancers, asthma, allergies, and neurological outcomes (Blair et al., 2015; Cosselman et al., 2015; Curl et al., 2020; Fuhrimann et al., 2021; Parks et al., 2019). This shift results also in healthier food chain conditions, less environmental contamination, and fewer effects on non-target organisms, enhancing safety for soil microorganisms as well (Singh et al., 2018; Tudi et al., 2022).

Using PF techniques enhances crop monitoring, providing farmers with more accurate field data to identify plants that need spraying to prevent rot or fertilising to increase yield. This helps to prevent food loss and hence reduce hunger, a key objective of the Global Goals and the 2030 Agenda for Sustainable Development (United Nations, 2015a).

7.3.1.2 Benefits to society

The adoption of advanced technologies, such as UAVs in PF, offers numerous societal benefits, extending beyond farmers to the wider community. They have significant social advantages, particularly for younger generations (White, 2012), by enhancing the viability of rural areas, preventing depopulation, and fostering resilient communities.

Moreover, new employment opportunities are generated. As digitalisation progresses, there is an increasing need for roles related to engineering, data analysis, technology maintenance, and digital marketing within the agricultural sector (Cunha et al., 2020). These jobs not only provide employment but also drive economic development in rural areas (Paniagua, 2020), making them more attractive places to live and work. The economic growth in these regions boosts other sectors as well, requiring additional services such as hospitals, schools, and shops to accompany the expanding population, which in turn creates further employment opportunities. Agritourism brings additional economic advantages. It generates income by drawing visitors interested in learning about farming techniques, experiencing rural life and being in closer contact with nature (Ciolac et al., 2020). This engagement fosters a deeper appreciation of agricultural heritage and cultural preservation, thereby strengthening community identity and cohesion and also leading to employment opportunities (Sardaro et al., 2021; Setten, 2006).

Technological integration in farming enhances community resilience by promoting sustainable agricultural practices that safeguard the environment. These practices ensure long-term food security by improving the reliability and quality of food production (Agnoletti and Santoro, 2022), essential for the stability and growth of rural areas. Another significant benefit of PF is sustainable growth in rural communities. These methods optimise resource use and minimise environmental impact, contributing to overall ecosystem health (Hibbard and Lurie, 2013). This sustainable approach ensures that rural areas can thrive economically while preserving their natural resources for future generations.

7.3.2 Environmental advantages

By reducing the amount of chemicals applied, the volume of pesticides reaching the soil is lowered. Consequently, fewer soil microorganisms are exposed to harmful chemicals, positively affecting their population density (Kalia and Gosal, 2011). These microorganisms, together with plants through photosynthesis, play a crucial role in CO_2 fixation (Chen et al., 2003; Osmond et al., 1982). Their proliferation in soils is vital for combating climate change (Jansson and Hofmockel, 2020). Implementing regenerative agriculture principles (Schreefel et al., 2020), which include minimal soil disturbance, like lowering the amount of chemical to the soil, among other practices, enhances soil health, boosts biodiversity, and prevents soil erosion. In this way, resilience is increased and greenhouse gas emissions are reduced. Improving soil health is critical as it can reverse global warming (Allen et al., 2011; Lal, 2016) and increase productivity (Nunes et al., 2018).

Using machines like UAVs or UGVs for chemical applications reduces the required pesticide volume and enhances targeting, thereby lowering drift (Brown and Giles, 2018; Hall and Fox, 1996), which refers to pesticide particles that, due to air currents, miss the target and end up in the surrounding environment, making the production process less environmentally friendly. Besides, the reduction in pesticides benefits the broader population and environment by decreasing emissions of volatile organic compounds (VOCs) (Razo-Belman and Ozuna, 2023), as well as CO_2 from their production (Lal, 2004), which is a GHG with effects on climate change.

Using electric-powered machines such as UAVs or UGVs reduces the carbon footprint of chemical applications. As observed in Table 3.1, tractors require 12 litres of fuel per hour, whereas a UAV only uses 1566 Wh and a UGV consumes 1924 Wh. This results in lower CO_2 emissions. Lastly, there is the potential to charge these machines' batteries with renewable energy sources (Banguero et al., 2018), further decreasing the environmental impact of chemical applications. However, the production of electric-powered batteries needs to be assessed in terms of social and environmental aspects to validate the sustainability of these platforms compared to traditional tractors from a global perspective. This analysis is further remarked in *Section 7.4.3.2*.

7.4 Analysis of the limitations encountered and future prospects

This thesis has provided successful results to the scientific community, society and the environment, as remarked in *Section 7.3*, demonstrating significant advancements in the domain of PF through integration with electric-powered technologies. However, several obstacles were encountered during the research process.

7.4.1 Data collection, annotation, and interpretation

An important constraint is that large volumes of data are essential for training object detection and tracking algorithms, necessitating substantial storage capacity (Ghosh et al., 2018). The computational demands of DL algorithms present a significant challenge, especially since not all researchers have extensive computational resources. UAVs collect vast amounts of data, leading to potential data overload (Dietzmann and Duan, 2022) and requiring robust management and analysis tools. To address these challenges, there are several solutions that can be employed, all presenting advantages and disadvantages and hence, they should be applied to the specific use case to verify which is the most appropriate one:

- Data summarisation (Hesabi et al., 2015) refines large datasets into key features, reducing volume while retaining essential insights, although there is the risk of losing detail and introducing bias.

- Data pruning (Saseendran et al., 2019) removes redundant or less critical information, decreasing storage needs, despite that it can inadvertently eliminate valuable data and is complex to execute.

- Data compression (Correa et al., 2022) reduces file sizes though it can degrade data quality and add computational overhead.

- Edge computing (Chen and Ran, 2019) processes data closer to its source, reducing the need for central storage, still, it requires careful design and integration and raises security concerns.

- Integrating IoT devices for real-time data processing adds complexity and resource demand but allows immediate data handling (J. Xu et al., 2022).

Once the data is processed, it can be uploaded to cloud storage to ensure sufficient space for new data. These methods remark on the need for a balanced approach to data management, ensuring benefits without compromising data quality and usability. Moreover, these solutions assume good connectivity, which is not always true in rural areas.

Furthermore, *Section 2.4.2.3* identified relevant obstacles for Woody crops, which were fruit occlusion and data scarcity. Fruit occlusion, caused by dense canopies (Guadagna et al., 2023; L. Shen et al., 2023) or by leaves and branches (Table 6.3), was addressed in this thesis through the development of a multi-angle approach (Figure 5.7).

To combat data scarcity, this thesis provided three open-source datasets (Ariza-Sentís et al., 2024b, 2023e; Vélez et al., 2023b), underscoring the importance of public datasets. This allows other researchers to validate and reproduce the developed research. Also, along with the dataset of (Santos et al., 2019) (Figure 2.5), they address the lack of public vineyard datasets. Data acquisition is a significant challenge as it is time consuming and expensive (Omar and Nehdi, 2016), requiring the rental or purchase of equipment such as platforms like UAVs and sensors. In addition, object detection and tracking algorithms necessitate labelled datasets, often done manually (Schreiner et al., 2006) (Figure 4.3) due to the absence of baseline datasets for AI-powered annotation tools to learn from (*Section 7.2*). Effective training of these algorithms requires large, high-quality datasets to avoid overfitting (Santos and Papa, 2022). In agriculture, the need for extensive data is even more critical due to its dynamic nature, with varying landscapes and unpredictable weather adding complexity to the algorithms' ability to generalise. Moreover, the wide variety of colours and shapes of agricultural objects (Bonneau et al., 2020; Xu and Mishra, 2022) complicates the development of a general algorithm for detecting and tracking multiple agricultural identities. Ensuring data and annotations are accurate and suitable for analysis is crucial, as poor data quality can limit detection and tracking performance (Cap et al., 2022; Shorten and Khoshgoftaar, 2019).

Providing open-source datasets is the most effective solution, as they can validate the author's research and generalise the developed algorithms to different latitudes and lighting conditions. If these datasets include labels, they can train automatic image labellers, reducing the time and error-prone task of manual annotations for other researchers. Once there are several public datasets addressing the need for diversity, image augmentation techniques (Shorten and Khoshgoftaar, 2019) and synthetic data (Raghunathan, 2021) can be used to expand these datasets, provided they produce realistic conditions.

After data collection and annotation, it is important to properly analyse and interpret the data, which requires technical expertise. To mitigate this, it is crucial to provide open-source code, enabling researchers and companies to develop applications that offer automatic interpretation of results as performed in *Chapter 3* with the Botrytis Bunch Rot algorithm (Figure 3.2), ideally in near real-time. This approach increases farmers' willingness to adopt these technologies by minimising the time investment needed to learn and apply those tools to their fields, making advanced agricultural technologies more accessible and effective.

7.4.2 Detection and Tracking

Chapter 2 and Section 7.2 indicated that one of the primary challenges of object detection and tracking algorithms applied to agriculture is environmental similarity and lighting. This includes atmospheric distortions and shadows, which hide objects of interest and alter their visual characteristics (Zhai et al., 2020). This issue is particularly pronounced in aerial images and videos acquired by UAVs, which are also affected by cloud cover and other unfavourable weather conditions (Porikli, 2006). These factors complicate the detection process, especially in distinguishing between similar objects such as weeds and crops (Dyrmann et al., 2017, 2016) or with their surrounding canopy (Bargoti and Underwood, 2017b; Chen et al., 2017) (Figure 4.6), which makes fruit counting challenging, leading to potential inaccuracies in their estimation. Furthermore, intense sunlight and the motion blurry effect complicate the detection and tracking tasks. All these conditions affect the accuracy of results.

However, these conditions are common in traditional vineyard regions, especially during the summer production campaign. Therefore, data should be collected on clear sky days to avoid changes in reflectance due to clouds. Flights should occur when the sun is mostly overhead to minimise shadows unless they are used for purposes such as obtaining the LAI as described by (Vélez et al., 2021). In cases of intense sunlight, multiple flights at different times may help identify when the colour contrast between grape bunches and the surrounding canopy is greatest, enhancing the clear identification of grape bunches.

An additional complication identified during this thesis (*Chapter 6*) is the acquisition of data from multiple angles, which resulted in blurred frames due to UAV motion (Ribeiro-Gomes et al., 2016) during the UAV change of perspectives (Table 6.4). This led to low-quality images, affecting detection and tracking metrics. The detection and tracking metrics were suboptimal for both single and multiple-angle perspectives (*Chapters 4 and 6*), although the latter showed slight improvement (Table 6.2). These metrics were significantly lower compared to similar studies conducted in orchards (de Jong et al., 2022) or within the scope of PF, such as livestock surveillance (Huang et al., 2023). As already discussed, several factors such as colour similarity and illumination conditions, affected those metrics.

It is important to note that tracking involves monitoring the position of an object over time. While tracking is suitable for moving objects, such as livestock (Figure 2.8), it may not be the most effective approach for counting static objects like grape bunches. Therefore, alternative methods for fruit detection should be explored, such as generating a panoramic image of the vineyard row through image stitching and performing detection on that picture (Y. Zhou et al., 2019). This approach would require less computational time than tracking, potentially enabling real-time applications. However, due to time constraints during the development of this thesis, these alternatives were not further investigated. It should be emphasised that the multiple-angle methodology designed in this thesis can also be combined with image stitching, as the vineyard would still be affected by occlusion.

7.4.3 Regulations

7.4.3.1 Aerial spraying and phytosanitary doses

In addition to the previously mentioned challenges, there are further obstacles to the integration of PF with electric-powered technologies. One major issue is the prohibition under EU Directive 2009/128/CE (Official Journal of the European Union, 2019), specifically Article 9, on aerial spraying of phytosanitary, which includes the use of UAVs. Using drones for crop spraying in precision agriculture can substantially lower the volume of chemicals required, which also enhances operator safety and reduces environmental hazards (Hanif et al., 2022).

As it has been analysed in *Chapter 3*, conventional field sprayers apply larger doses of chemicals per hectare compared to UAVs (*Section 3.3.3.4*). For instance, with Botrytis Bunch Rot, the recommendation of the seller (Bayer, 2023) suggested around 1000-1500 litres per hectare, whereas this amount was drastically reduced to 40 litres when spraying with a UAV (Ibericadron, 2023). Technically, application rates can be lower than

40 litres, influenced by whether the system is hydraulic or uses controlled droplet technology, the latter offering precise droplet size control (Chen et al., 2020).

The potential for significantly reduced spray rates is encouraging, yet practical experience remains limited due to current regulations. Existing pesticide formulations have not been extensively tested at these lower rates to ensure effectiveness. Field trials are crucial to establish safe guidelines for drone-based pesticide applications (Xin et al., 2018). The behaviour of components at low volumes is notably different from conventional tank mixes, increasing the risk of inadequate coverage (Berger-Neto et al., 2017) and potential exposure to high pesticide concentrations, which can severely affect photosynthesis and cause phytotoxicity, crop damage, and yield loss (Gautam et al., 2023; Hasanuzzaman et al., 2020). Accurate dosing is essential, and future reductions in doses will depend on proving more efficient application techniques than traditional hydraulic systems through rigorous trials and evaluations. Moreover, the concentration and viscosity of spray mixtures are critical; higher component density requires recalibrating the drone's application unit to ensure the proper dose of active ingredients (Matthews et al., 2014).

Therefore, EU regulations need to harmonise with environmental benefits and the Global Goals and 2030 Agenda to decrease chemical use and support sustainable food production (United Nations, 2015a). Investing in research on precise UAV spraying is essential to fully exploit their advantages and understand their potential with lower volumes of current phytosanitary products while enhancing sustainability (Hilz and Vermeer, 2013).

7.4.3.2 Electric-powered platforms

It is important to note that the technology life cycle includes the recycling or reusing of the materials from which they are made. Recycling batteries, particularly lithium-ion batteries, which are the most common for UAVs, UGVs, and solar panels (Deng and Aifantis, 2023; C. Xiao et al., 2023), presents significant challenges due to the complexity of the recycling process and potential environmental hazards (Y. Wang et al., 2021). These batteries contain various toxic materials, including lithium, cobalt, and nickel, which require specialised handling and processing to safely recover. The recycling process is energy-intensive and often not cost-effective, leading to a low recycling rate (Velázquez-

Martínez et al., 2019). Moreover, improper disposal of lithium-ion batteries can result in environmental contamination and pose fire hazards due to their reactive nature (Krüger et al., 2014; R. Zhang et al., 2020).

The mining of lithium also poses substantial environmental and social problems (Dunlap and Riquito, 2023; Ribeiro et al., 2021). Lithium extraction, primarily from brine in South America or hard rock mining in Australia, consumes vast amounts of water, leading to water scarcity in already arid regions. It also causes significant landscape disruption and environmental degradation, including soil contamination and loss of biodiversity (Parker et al., 2024). Furthermore, mining operations often have detrimental impacts on local communities, including displacement and adverse health effects (Egbue, 2012).

To address these issues and truly initiate a green revolution and stay that electric-powered platforms are more sustainable than tractors, it is crucial to invest in research on alternative materials for batteries that are more environmentally friendly and sustainable. There must also be stricter regulations and policies governing both the mining and recycling processes to minimise their environmental impact. Strategies that protect local communities and encourage innovation in battery technology are essential to achieve a more sustainable and environmentally responsible future.

7.4.3.3 Future of UAVs and AI in European Agriculture

According to the EU 2019/947 and EU 2019/945 regulations, all UAV missions in the EU necessitate the physical presence of a pilot, regardless of the operational category. For the Open Category, the pilot must maintain a visual line of sight (VLOS) with the UAV. In the Specific Category, operations can also be managed using a remote pilot station, subject to authorisation and risk assessments. The Certified Category, which includes higher-risk operations, requires adherence to stringent certification and compliance standards. This framework ensures the safety of users and the surroundings. In contexts such as agricultural fields, where the UAV pilot may often be the only person present, tailored regulations could support the advancement of UAV applications in PF, balancing safety with operational efficiency.

In the European Union, the application of AI in agriculture should continue as long as it complies with regulatory standards set by the EU AI Act, which aims to ensure AI systems are trustworthy and human-centric. Agriculture has not been explicitly categorised under any specific risk level, leading to potential confusion. The EU AI Act is not sector-specific but would benefit from clarifying individual impacts, especially since sectors like agriculture have different interactions with humans compared to other industries, suggesting the need for tailored regulations per sector.

In addition, to demonstrate the efficacy and applicability of UAVs and other integrating devices such as UGVs in real farm settings, EU-funded projects with higher Technology Readiness Levels (TRL) are essential. These projects should focus on evaluating the long-term viability of these equipment, including a thorough examination of their costs (da Silveira et al., 2021), maintenance requirements, and the potential benefits they offer, such as early yield prediction and reduced chemical use. Comprehensive research into these aspects will be crucial in determining the investmentworthiness of this technology and facilitating its adoption in the farming sector. Lastly, educating farmers on the benefits of PF and providing clear demonstrations of the long-term benefits are vital for achieving widespread adoption (Abbasi et al., 2022). These advancements will enhance the precision and sustainability of high-value crop management, ultimately benefiting farmers, society, and the environment.

7.5 Conclusions

Precision farming is undergoing a revolution, and it is essential that this transformation is properly accompanied by technological advancements and research to enhance sustainability and increase food productivity. Resource optimisation through precise spraying and early yield prediction are already providing relevant benefits to farmers, society, and the environment. Our research indicated that optimising data collection methods before applying DL algorithms is crucial to avoid fruit occlusion and enhance algorithm metrics. We developed a two-phase strategy that included: i) obtaining a general aerial view of the field while analysing the biophysical environment, and ii) performing a closer flight with multiple perspectives to capture specific crop characteristics while avoiding fruit occlusion. This approach resulted in higher grape bunch detection metrics and more accurate fruit counting, which can be correlated with more accurate yield prediction and optimal spraying of the entire grape bunch surface. Our findings highlight the need for AI to consider the living nature of plants, requiring tailored and dynamic monitoring strategies.

Nevertheless, significant challenges remain in its integration with precision farming. These obstacles include the scarcity of open-source data, lack of automation and generalisation, regulatory hurdles in the EU, and the necessity for research applied to real farm conditions. While substantial progress has been made in other knowledge domains since the origin of AI, it is now crucial to apply this learned experience to reinforce the importance and development of the primary sector.

References

Abade, A., Porto, L.F., Ferreira, P.A., de Barros Vidal, F., 2022. NemaNet: A convolutional neural network model for identification of soybean nematodes. Biosyst. Eng. 213, 39–62. https://doi.org/10.1016/j.biosystemseng.2021.11.016

Abbasi, R., Martinez, P., Ahmad, R., 2022. The digitization of agricultural industry – a systematic literature review on agriculture 4.0. Smart Agric. Technol. 2, 100042. https://doi.org/10.1016/j.atech.2022.100042

Abbaspour, M., Masnadi-Shirazi, M.A., 2022. Online multi-object tracking with δ-GLMB filter based on occlusion and identity switch handling. Image Vis. Comput. 127, 104553. https://doi.org/10.1016/j.imavis.2022.104553

Abdullahi, H.S., Mahieddine, F., Sheriff, R.E., 2015. Technology Impact on Agricultural Productivity: A Review of Precision agriculture Using Unmanned Aerial Vehicles, in: Pillai, P., Hu, Y.F., Otung, I., Giambene, G. (Eds.), Wireless and Satellite Systems. Springer International Publishing, Cham, pp. 388–400. https://doi.org/10.1007/978-3-319-25479-1_29

Abdulridha, J., Ampatzidis, Y., Roberts, P., Kakarla, S.C., 2020. Detecting powdery mildew disease in squash at different stages using UAV-based hyperspectral imaging and artificial intelligence. Biosyst. Eng. 197, 135–148. https://doi.org/10.1016/j.biosystemseng.2020.07.001

Acharya, P., Burgers, T., Nguyen, K.-D., 2022. AI-enabled droplet detection and tracking for agricultural spraying systems. Comput. Electron. Agric. 202, 107325. https://doi.org/10.1016/j.compag.2022.107325

Acosta, M., Pena, J., Sherafat, A., Gonzalez, C., Sherman, T., Bhandari, S., Raheja, A., 2024. Investigating the potential of UAV-based hyperspectral sensor in detecting powdery mildew in grapes, in: Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IX. Presented at the Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IX, SPIE, pp. 26–34. https://doi.org/10.1117/12.3014667

Adli, H.K., Remli, M.A., Wan Salihin Wong, K.N.S., Ismail, N.A., González-Briones, A., Corchado, J.M., Mohamad, M.S., 2023. Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review. Sensors 23, 3752. https://doi.org/10.3390/s23073752

Aggarwal, S., Kumar, N., 2020. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. Comput. Commun. 149, 270–299. https://doi.org/10.1016/j.comcom.2019.10.014

Agnoletti, M., Santoro, A., 2022. Agricultural heritage systems and agrobiodiversity. Biodivers. Conserv. 31, 2231–2241. https://doi.org/10.1007/s10531-022-02460-3

Aguiar, A.S., Magalhães, S.A., dos Santos, F.N., Castro, L., Pinho, T., Valente, J., Martins, R., Boaventura-Cunha, J., 2021. Grape Bunch Detection at Different Growth Stages Using Deep Learning Quantized Models. Agronomy 11, 1890. https://doi.org/10.3390/agronomy11091890

Aguilera, E., Guzmán, G.I., González de Molina, M., Soto, D., Infante-Amate, J., 2019. From animals to machines. The impact of mechanization on the carbon footprint of traction in Spanish agriculture: 1900–2014. J. Clean. Prod. 221, 295–305. https://doi.org/10.1016/j.jclepro.2019.02.247

Ahmed, I., 1976. The Green Revolution and Tractorisation - Their Mutual Relations and Socio-Economic Effects. Int. Labour Rev. 114, 83.

Ahmed, Sk.A., Dogra, D.P., Kar, S., Roy, P.P., 2019. Trajectory-Based Surveillance Analysis: A Survey. IEEE Trans. Circuits Syst. Video Technol. 29, 1985–1997. https://doi.org/10.1109/TCSVT.2018.2857489

Akbari, Y., Almaadeed, N., Al-ma'adeed, S., Elharrouss, O., 2021. Applications, databases and open computer vision research from drone videos and images: a survey. Artif. Intell. Rev. 54. https://doi.org/10.1007/s10462-020-09943-1

Akyon, F.C., Eryuksel, O., Ozfuttu, K.A., Altinuc, S.O., 2021. Track Boosting and Synthetic Data Aided Drone Detection. 2021 17th IEEE Int. Conf. Adv. Video Signal Based Surveill. AVSS 1–5. https://doi.org/10.1109/AVSS52988.2021.9663759

Alam, M.S., Alam, M., Tufail, M., Khan, M.U., Güneş, A., Salah, B., Nasir, F.E., Saleem, W., Khan, M.T., 2022. TobSet: A New Tobacco Crop and Weeds Image Dataset and Its Utilization for Vision-Based Spraying by Agricultural Robots. Appl. Sci. 12, 1308. https://doi.org/10.3390/app12031308

Alanezi, M.A., Shahriar, M.S., Hasan, Md.B., Ahmed, S., Sha'aban, Y.A., Bouchekara, H.R.E.H., 2022. Livestock Management With Unmanned Aerial Vehicles: A Review. IEEE Access 10, 45001–45028. https://doi.org/10.1109/ACCESS.2022.3168295

Albetis, J., Duthoit, S., Guttler, F., Jacquin, A., Goulard, M., Poilvé, H., Féret, J.-B., Dedieu, G., 2017. Detection of Flavescence dorée Grapevine Disease Using Unmanned Aerial Vehicle (UAV) Multispectral Imagery. Remote Sens. 9, 308. https://doi.org/10.3390/rs9040308

Ali, M., Deo, R.C., Xiang, Y., Prasad, R., Li, J., Farooque, A., Yaseen, Z.M., 2022. Coupled online sequential extreme learning machine model with ant colony optimization algorithm for wheat yield prediction. Sci. Rep. 12, 5488. https://doi.org/10.1038/s41598-022-09482-5

Ali, Z.A., Deng, D., Kashif Shaikh, M., Hasan, R., Aamir Khan, M., 2023a. AI-Based UAV Swarms for Monitoring and Disease Identification of Brassica Plants Using Machine Learning: A Review. Comput. Syst. Sci. Eng. 0, 1–34. https://doi.org/10.32604/csse.2023.041866

Ali, Z.A., Yang, C., Israr, A., Zhu, Q., 2023b. A Comprehensive Review of Scab Disease Detection on Rosaceae Family Fruits via UAV Imagery. Drones 7, 97. https://doi.org/10.3390/drones7020097

Ali, Z.A., Zhangang, H., Hang, W.B., 2021. Cooperative Path planning of Multiple UAVs by using Max–Min Ant Colony Optimization along with Cauchy Mutant Operator. Fluct. Noise Lett. 20, 2150002. https://doi.org/10.1142/S0219477521500024

Ali, Z.A., Zhangang, H., Zhengru, D., 2023c. Path planning of multiple UAVs using MMACO and DE algorithm in dynamic environment. Meas. Control 56, 459–469. https://doi.org/10.1177/0020294020915727

Alibabaei, K., Gaspar, P.D., Lima, T.M., Campos, R.M., Girão, I., Monteiro, J., Lopes, C.M., 2022. A Review of the Challenges of Using Deep Learning Algorithms to Support Decision-Making in Agricultural Activities. Remote Sens. 14, 638. https://doi.org/10.3390/rs14030638

Allen, D.E., Singh, B.P., Dalal, R.C., 2011. Soil Health Indicators Under Climate Change: A Review of Current Knowledge, in: Singh, B.P., Cowie, A.L., Chan, K.Y. (Eds.), Soil Health and Climate Change. Springer, Berlin, Heidelberg, pp. 25–45. https://doi.org/10.1007/978-3-642-20256-8_2

Alpaydin, E., 2021. Machine Learning. MIT Press.

AL-Saddik, H., Simon, J.-C., Cointault, F., 2017. Development of Spectral Disease Indices for 'Flavescence Dorée' Grapevine Disease Identification. Sensors 17, 2772. https://doi.org/10.3390/s17122772

Alyassi, R., Khonji, M., Karapetyan, A., Chau, S.C.-K., Elbassioni, K., Tseng, C.-M., 2023. Autonomous Recharging and Flight Mission Planning for Battery-operated Autonomous Drones. IEEE Trans. Autom. Sci. Eng. 20, 1034–1046. https://doi.org/10.1109/TASE.2022.3175565

Amrani, A., Sohel, F., Diepeveen, D., Murray, D., Jones, M.G.K., 2023. Deep learning-based detection of aphid colonies on plants from a reconstructed Brassica image dataset. Comput. Electron. Agric. 205, 107587. https://doi.org/10.1016/j.compag.2022.107587

Amrouche, A., Bentrcia, Y., Abed, A., Hezil, N., 2022. Vehicle Detection and Tracking in Real-time using YOLOv4-tiny, in: 2022 7th International Conference on Image and Signal Processing and Their Applications (ISPA). Presented at the 2022 7th International Conference on Image and Signal Processing and their Applications (ISPA), pp. 1–5. https://doi.org/10.1109/ISPA54004.2022.9786330

Apolo-Apolo, O.E., Martínez-Guanter, J., Egea, G., Raja, P., Pérez-Ruiz, M., 2020. Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV. Eur. J. Agron. 115, 126030. https://doi.org/10.1016/j.eja.2020.126030

Ara, I., Turner, L., Harrison, M.T., Monjardino, M., deVoil, P., Rodriguez, D., 2021. Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. Agric. Water Manag. 257, 107161. https://doi.org/10.1016/j.agwat.2021.107161

Ariza-Sentís, M., Baja, H., Vélez, S., Valente, J., 2023a. Object detection and tracking on UAV RGB videos for early extraction of grape phenotypic traits. Comput. Electron. Agric. 211, 108051. https://doi.org/10.1016/j.compag.2023.108051

Ariza-Sentís, M., Valente, J., Kooistra, L., Kramer, H., Mücher, S., 2023b. Estimation of spinach (Spinacia oleracea) seed yield with 2D UAV data and deep learning. Smart Agric. Technol. 3, 100129. https://doi.org/10.1016/j.atech.2022.100129

Ariza-Sentís, M., Vélez, S., Baja, H., Valente, J., 2022. International Plant Phenotyping Symposium 2022 Conference Book. Presented at the International Plant Phenotyping Symposium, Wageningen, the Netherlands, p. 231.

Ariza-Sentís, M., Vélez, S., Baja, H., Valenti, R.G., Valente, J., 2024a. An aerial framework for Multi-View grape bunch detection and route Optimization using ACO. Comput. Electron. Agric. 221, 108972. https://doi.org/10.1016/j.compag.2024.108972

Ariza-Sentís, M., Vélez, S., Martínez-Peña, R., Baja, H., Valente, J., 2024b. Object detection and tracking in Precision farming: a systematic review. Comput. Electron. Agric. 219, 108757. https://doi.org/10.1016/j.compag.2024.108757

Ariza-Sentís, M., Vélez, S., Valente, J., 2023c. BBR: An open-source standard workflow based on biophysical crop parameters for automatic Botrytis cinerea assessment in vineyards. SoftwareX 24, 101542. https://doi.org/10.1016/j.softx.2023.101542

Ariza-Sentís, M., Vélez, S., Valente, J., 2023d. Dataset on UAV RGB videos acquired over a vineyard including bunch labels for object detection and tracking. Data Brief 46, 108848. https://doi.org/10.1016/j.dib.2022.108848

Ariza-Sentís, M., Wang, K., Cao, Z., Vélez, S., Valente, J., 2024c. GrapeMOTS: UAV vineyard dataset with MOTS grape bunch annotations recorded from multiple perspectives for enhanced object detection and tracking. Data Brief 54, 110432. https://doi.org/10.1016/j.dib.2024.110432

Arjovsky, M., Bottou, L., 2017. Towards Principled Methods for Training Generative Adversarial Networks. https://doi.org/10.48550/arXiv.1701.04862

Auernhammer, H., 2001. Precision farming - The environmental challenge. Comput. Electron. Agric. 30, 31–43. https://doi.org/10.1016/S0168-1699(00)00153-8

Azadi, H., Ho, P., Hasfiati, L., 2011. Agricultural land conversion drivers: A comparison between less developed, developing and developed countries. Land Degrad. Dev. 22, 596–604. https://doi.org/10.1002/ldr.1037

B., S., Tom, A.J., George, S.N., 2019. Simultaneous denoising and moving object detection using low rank approximation. Future Gener. Comput. Syst. 90, 198–210. https://doi.org/10.1016/j.future.2018.07.065

Babaee, M., Li, Z., Rigoll, G., 2018. Occlusion Handling in Tracking Multiple People Using RNN, in: 2018 25th IEEE International Conference on Image Processing (ICIP). Presented at the 2018 25th IEEE International Conference on Image Processing (ICIP), pp. 2715–2719. https://doi.org/10.1109/ICIP.2018.8451140

Babu, K.M., Raghunadh, M.V., 2016. Vehicle number plate detection and recognition using bounding box method, in: 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT). Presented at the 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), pp. 106–110. https://doi.org/10.1109/ICACCCT.2016.7831610

Bagheri Tolabi, H., Lashkar Ara, A., Hosseini, R., 2021. An enhanced particle swarm optimization algorithm to solve probabilistic load flow problem in a micro-grid. Appl. Intell. 51, 1645–1668. https://doi.org/10.1007/s10489-020-01872-4

Bakhtiari, A., Navid, H., Mehri, J., Berruto, R., Bochtis, D.D., 2013. Operations planning for agricultural harvesters using ant colony optimization. Span. J. Agric. Res. 11, 652–660. https://doi.org/10.5424/sjar/2013113-3865

Bakhtiari, A.A., Navid, H., Mehri, J., Bochtis, D.D., 2011. Optimal route planning of agricultural field operations using ant colony optimization. Agric. Eng. Int. CIGR J. 13, 1–10.

Balampanis, F., Maza, I., Ollero, A., 2017. Coastal Areas Division and Coverage with Multiple UAVs for Remote Sensing. Sensors 17, 808. https://doi.org/10.3390/s17040808

Balampanis, F., Maza, I., Ollero, A., 2016. Area decomposition, partition and coverage with multiple remotely piloted aircraft systems operating in coastal regions, in: 2016 International Conference on Unmanned Aircraft Systems (ICUAS). Presented at the 2016 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 275–283. https://doi.org/10.1109/ICUAS.2016.7502602

Baldwin, N., 2011. Tractors: 1880s to 1980s. Bloomsbury Publishing.

Banguero, E., Correcher, A., Pérez-Navarro, Á., Morant, F., Aristizabal, A., 2018. A Review on Battery Charging and Discharging Control Strategies: Application to Renewable Energy Systems. Energies 11, 1021. https://doi.org/10.3390/en11041021

Bargoti, S., Underwood, J., 2017a. Deep fruit detection in orchards, in: 2017 IEEE International Conference on Robotics and Automation (ICRA). Presented at the 2017 IEEE International Conference on Robotics and Automation (ICRA), pp. 3626–3633. https://doi.org/10.1109/ICRA.2017.7989417

Bargoti, S., Underwood, J., 2017b. Deep fruit detection in orchards, in: 2017 IEEE International Conference on Robotics and Automation (ICRA). Presented at the 2017 IEEE International Conference on Robotics and Automation (ICRA), pp. 3626–3633. https://doi.org/10.1109/ICRA.2017.7989417

Bari, B.S., Islam, M.N., Rashid, M., Hasan, M.J., Razman, M.A.M., Musa, R.M., Nasir, A.F.A., Majeed, A.P.P.A., 2021. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. PeerJ Comput. Sci. 7, e432. https://doi.org/10.7717/peerj-cs.432

Basiri, A., Mariani, V., Silano, G., Aatif, M., Iannelli, L., Glielmo, L., 2022. A survey on the application of path-planning algorithms for multi-rotor UAVs in precision agriculture. J. Navig. 75, 364–383. https://doi.org/10.1017/S0373463321000825

Batey, T., 2009. Soil compaction and soil management – a review. Soil Use Manag. 25, 335–345. https://doi.org/10.1111/j.1475-2743.2009.00236.x

Bauer, A., Bostrom, A.G., Ball, J., Applegate, C., Cheng, T., Laycock, S., Rojas, S.M., Kirwan, J., Zhou, J., 2019. Combining computer vision and deep learning to enable ultra-scale aerial phenotyping and precision agriculture: A case study of lettuce production. Hortic. Res. 6, 70. https://doi.org/10.1038/s41438-019-0151-5

Baweja, P., Kumar, S., Kumar, G., 2020. Fertilizers and Pesticides: Their Impact on Soil Health and Environment, in: Giri, B., Varma, A. (Eds.), Soil Health, Soil Biology. Springer International Publishing, Cham, pp. 265–285. https://doi.org/10.1007/978-3-030-44364-1_15

Bayer, 2023. Serenade® ASO - Crop Science Spain [WWW Document]. URL https://www.cropscience.bayer.es/Productos/Fungicidas/Serenade-ASO (accessed 3.18.24).

Becce, L., Bloise, N., Guglieri, G., 2021. Optimal Path planning for Autonomous Spraying UAS framework in Precision agriculture, in: 2021 International Conference on Unmanned Aircraft Systems (ICUAS). Presented at the 2021 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 698–707. https://doi.org/10.1109/ICUAS51884.2021.9476690

Bellvert, J., Marsal, J., Girona, J., Zarco-Tejada, P.J., 2015. Seasonal evolution of crop water stress index in grapevine varieties determined with high-resolution remote sensing thermal imagery. Irrig. Sci. 33, 81–93. https://doi.org/10.1007/s00271-014-0456-y

Benet, B., Lenain, R., 2017. Multi-sensor fusion method for crop row tracking and traversability operations, in: Conférence AXEMA-EURAGENG 2017, Conférence AXEMA-EURAGENG 2017. Paris, France, p. 10 p.

Berger-Neto, A., Jaccoud-Filho, D. de S., Wutzki, C.R., Tullio, H.E., Pierre, M.L.C., Manfron, F., Justino, A., 2017. Effect of spray droplet size, spray volume and fungicide on the control of white mold in soybeans. Crop Prot. 92, 190–197. https://doi.org/10.1016/j.cropro.2016.10.016

Blackmore, S., 1994. Precision farming: An Introduction. Outlook Agric. 23, 275–280. https://doi.org/10.1177/003072709402300407

Blair, A., Ritz, B., Wesseling, C., Freeman, L.B., 2015. Pesticides and human health. Occup. Environ. Med. 72, 81–82. https://doi.org/10.1136/oemed-2014-102454

Bongiovanni, R., Lowenberg-Deboer, J., 2004. Precision agriculture and sustainability. Precis. Agric. 5, 359–387. https://doi.org/10.1023/B:PRAG.0000040806.39604.aa

Bonneau, M., Vayssade, J.-A., Troupe, W., Arquet, R., 2020. Outdoor animal tracking combining neural network and time-lapse cameras. Comput. Electron. Agric. 168, 105150. https://doi.org/10.1016/j.compag.2019.105150

Boogaard, F.P., Rongen, K.S.A.H., Kootstra, G.W., 2020. Robust node detection and tracking in fruit-vegetable crops using deep learning and multi-view imaging. Biosyst. Eng. 192, 117–132. https://doi.org/10.1016/j.biosystemseng.2020.01.023

Boss, P. k., Kalua, C. m., Nicholson, E. l., Maffei, S. m., Böttcher, C., Davies, C., 2018. Fermentation of grapes throughout development identifies stages critical to the development of wine volatile composition. Aust. J. Grape Wine Res. 24, 24–37. https://doi.org/10.1111/ajgw.12296

Botta, A., Cavallone, P., Baglieri, L., Colucci, G., Tagliavini, L., Quaglia, G., 2022. A Review of Robots, Perception, and Tasks in Precision agriculture. Appl. Mech. 3, 830–854. https://doi.org/10.3390/applmech3030049

Bouguettaya, A., Zarzour, H., Kechida, A., Taberkit, A.M., 2022. Deep learning techniques to classify agricultural crops through UAV imagery: a review. Neural Comput. Appl. 34, 9511–9536. https://doi.org/10.1007/s00521-022-07104-9

Brock, A., Donahue, J., Simonyan, K., 2019. Large Scale GAN Training for High Fidelity Natural Image Synthesis. https://doi.org/10.48550/arXiv.1809.11096

Brown, C.R., Giles, D.K., 2018. Measurement of pesticide drift from unmanned aerial vehicle application to a vineyard. Am. Soc. Agric. Biol. Eng. 61, 1539–1546. https://doi.org/10.13031/trans.12672

Brunet, H., Creach, P., Concordet, D., 2023. Optimal estimation of broiler movement for commercial tracking. Smart Agric. Technol. 3, 100113. https://doi.org/10.1016/j.atech.2022.100113

Bullinger, S., Bodensteiner, C., Arens, M., 2017. Instance Flow Based Online Multiple Object Tracking.

Burr, T., 2008. Pattern Recognition and Machine Learning. J. Am. Stat. Assoc. 103, 886–887. https://doi.org/10.1198/jasa.2008.s236

Buunk, T., Vélez, S., Ariza-Sentís, M., Valente, J., 2023. Comparing Nadir and Oblique Thermal Imagery in UAV-Based 3D Crop Water Stress Index Applications for Precision viticulture with LiDAR Validation. Sensors 23, 8625. https://doi.org/10.3390/s23208625

Cabrera-Bosquet, L., Fournier, C., Brichet, N., Welcker, C., Suard, B., Tardieu, F., 2016. High-throughput estimation of incident light, light interception and radiation-use efficiency of thousands of plants in a phenotyping platform. New Phytol. 212, 269–281. https://doi.org/10.1111/nph.14027

Campos, J., Llop, J., Gallart, M., García-Ruiz, F., Gras, A., Salcedo, R., Gil, E., 2019. Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process. Precis. Agric. 20, 1136–1156. https://doi.org/10.1007/s11119-019-09643-z

Cao, Y., Chen, J., Zhang, Z., 2023. A sheep dynamic counting scheme based on the fusion between an improved-sparrow-search YOLOv5x-ECA model and few-shot deepsort algorithm. Comput. Electron. Agric. 206, 107696. https://doi.org/10.1016/j.compag.2023.107696

Cap, Q.H., Uga, H., Kagiwada, S., Iyatomi, H., 2022. LeafGAN: An Effective Data Augmentation Method for Practical Plant Disease Diagnosis. IEEE Trans. Autom. Sci. Eng. 19, 1258–1267. https://doi.org/10.1109/TASE.2020.3041499

Carreira, J., Zisserman, A., 2017. Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset, in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 4724–4733. https://doi.org/10.1109/CVPR.2017.502

Carvalho, F.P., 2017. Pesticides, environment, and food safety. Food Energy Secur. 6, 48–60. https://doi.org/10.1002/fes3.108

Castro, W., Marcato Junior, J., Polidoro, C., Osco, L.P., Gonçalves, W., Rodrigues, L., Santos, M., Jank, L., Barrios, S., Valle, C., Simeão, R., Carromeu, C., Silveira, E., Jorge, L.A. de C., Matsubara, E., 2020. Deep Learning Applied to Phenotyping of Biomass in Forages with UAV-Based RGB Imagery. Sensors 20, 4802. https://doi.org/10.3390/s20174802

Cavalaris, C., 2023. Chapter 10 - Energy efficiency for in-farm unmanned aerial system applications, in: Bochtis, D., Tagarakis, A.C., Kateris, D. (Eds.), Unmanned Aerial

Systems in Agriculture. Academic Press, pp. 231–244. https://doi.org/10.1016/B978-0-323-91940-1.00010-4
Chakraborty, S., Elangovan, D., Govindarajan, P.L., ELnaggar, M.F., Alrashed, M.M., Kamel, S., 2022. A Comprehensive Review of Path planning for Agricultural Ground Robots. Sustainability 14, 9156. https://doi.org/10.3390/su14159156
Chang, A., Yeom, J., Jung, J., Landivar, J., 2020. Comparison of Canopy Shape and Vegetation Indices of Citrus Trees Derived from UAV Multispectral Images for Characterization of Citrus Greening Disease. Remote Sens. 12, 4122. https://doi.org/10.3390/rs12244122
Chang, K.-C., Guo, Z.-W., 2018. The Monkeys are Coming — Design of Agricultural Damage Warning System by IoT-Based Objects Detection and Tracking, in: 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW). Presented at the 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), pp. 1–2. https://doi.org/10.1109/ICCE-China.2018.8448434
Chen, G., Zhu, H., Zhang, Y., 2003. Soil microbial activities and carbon and nitrogen fixation. Res. Microbiol. 154, 393–398. https://doi.org/10.1016/S0923-2508(03)00082-2
Chen, J., Ran, X., 2019. Deep Learning With Edge Computing: A Review. Proc. IEEE 107.
Chen, J., Wu, J., Wang, Z., Qiang, H., Cai, G., Tan, C., Zhao, C., 2021. Detecting ripe fruits under natural occlusion and illumination conditions. Comput. Electron. Agric. 190, 106450. https://doi.org/10.1016/j.compag.2021.106450
Chen, P., Li, W., Yao, S., Ma, C., Zhang, J., Wang, B., Zheng, C., Xie, C., Liang, D., 2021. Recognition and counting of wheat mites in wheat fields by a three-step deep learning method. Neurocomputing 437, 21–30. https://doi.org/10.1016/j.neucom.2020.07.140
Chen, S., Lan, Y., Zhou, Z., Ouyang, F., Wang, G., Huang, X., Deng, X., Cheng, S., 2020. Effect of Droplet Size Parameters on Droplet Deposition and Drift of Aerial Spraying by Using Plant Protection UAV. Agronomy 10, 195. https://doi.org/10.3390/agronomy10020195
Chen, S.W., Shivakumar, S.S., Dcunha, S., Das, J., Okon, E., Qu, C., Taylor, C.J., Kumar, V., 2017. Counting Apples and Oranges with Deep Learning: A Data-Driven Approach. IEEE Robot. Autom. Lett. 2, 781–788. https://doi.org/10.1109/LRA.2017.2651944
Chen, Y., An, X., Gao, S., Li, S., Kang, H., 2021. A Deep Learning-Based Vision System Combining Detection and Tracking for Fast On-Line Citrus Sorting. Front. Plant Sci. 12, 622062. https://doi.org/10.3389/fpls.2021.622062
Chen, Y., Lee, W.S., Gan, H., Peres, N., Fraisse, C., Zhang, Y., He, Y., 2019. Strawberry Yield Prediction Based on a Deep Neural Network Using High-Resolution Aerial Orthoimages. Remote Sens. 11, 1584. https://doi.org/10.3390/rs11131584
Chen, Y., Shang, N., 2021. Comparison of GA, ACO algorithm, and PSO algorithm for path optimization on free-form surfaces using coordinate measuring machines. Eng. Res. Express 3, 045039. https://doi.org/10.1088/2631-8695/ac3e13
Chodey, M.D., Noorullah Shariff, C., 2023. Pest detection via hybrid classification model with fuzzy C-means segmentation and proposed texture feature. Biomed. Signal Process. Control 84, 104710. https://doi.org/10.1016/j.bspc.2023.104710
Choset, H., Pignon, P., 1998. Coverage Path planning: The Boustrophedon Cellular Decomposition, in: Zelinsky, A. (Ed.), Field and Service Robotics. Springer, London, pp. 203–209. https://doi.org/10.1007/978-1-4471-1273-0_32
Christiansen, P., Nielsen, L., Steen, K., Jørgensen, R., Karstoft, H., 2016. DeepAnomaly: Combining Background Subtraction and Deep Learning for Detecting Obstacles

and Anomalies in an Agricultural Field. Sensors 16, 1904. https://doi.org/10.3390/s16111904
Chung, T.J., 2002. Computational Fluid Dynamics. Cambridge University Press.
Ciarfuglia, T.A., Motoi, I.M., Saraceni, L., Fawakherji, M., Sanfeliu, A., Nardi, D., 2023. Weakly and semi-supervised detection, segmentation and tracking of table grapes with limited and noisy data. Comput. Electron. Agric. 205, 107624. https://doi.org/10.1016/j.compag.2023.107624
Ciolac, R., Iancu, T., Brad, I., Popescu, G., Marin, D., Adamov, T., 2020. Agritourism Activity—A "Smart Chance" for Mountain Rural Environment's Sustainability. Sustainability 12, 6237. https://doi.org/10.3390/su12156237
Čirjak, D., Aleksi, I., Lemic, D., Pajač Živković, I., 2023. EfficientDet-4 Deep Neural Network-Based Remote Monitoring of Codling Moth Population for Early Damage Detection in Apple Orchard. Agriculture 13, 961. https://doi.org/10.3390/agriculture13050961
Cooper, J., Dobson, H., 2007. The benefits of pesticides to mankind and the environment. Crop Prot. 26, 1337–1348. https://doi.org/10.1016/j.cropro.2007.03.022
Correa, J.D.A., Pinto, A.S.R., Montez, C., 2022. Lossy Data Compression for IoT Sensors: A Review. Internet Things 19, 100516. https://doi.org/10.1016/j.iot.2022.100516
Cosselman, K.E., Navas-Acien, A., Kaufman, J.D., 2015. Environmental factors in cardiovascular disease. Nat. Rev. Cardiol. 12, 627–642. https://doi.org/10.1038/nrcardio.2015.152
Cossio-Montefinale, L., Ruiz-del-Solar, J., Verschae, R., 2024. Cherry CO Dataset: A Dataset for Cherry Detection, Segmentation and Maturity Recognition. IEEE Robot. Autom. Lett. 9, 5552–5558. https://doi.org/10.1109/LRA.2024.3393214
Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., Traore, D., 2022. Deep learning for precision agriculture: A bibliometric analysis. Intell. Syst. Appl. 16, 200102. https://doi.org/10.1016/j.iswa.2022.200102
Cunha, C.R., Gomes, J.P., Fernandes, J., Morais, E.P., 2020. Building Smart Rural Regions: Challenges and Opportunities, in: Rocha, Á., Adeli, H., Reis, L.P., Costanzo, S., Orovic, I., Moreira, F. (Eds.), Trends and Innovations in Information Systems and Technologies. Springer International Publishing, Cham, pp. 579–589. https://doi.org/10.1007/978-3-030-45697-9_56
Curl, C.L., Spivak, M., Phinney, R., Montrose, L., 2020. Synthetic Pesticides and Health in Vulnerable Populations: Agricultural Workers. Curr. Environ. Health Rep. 7, 13–29. https://doi.org/10.1007/s40572-020-00266-5
CVAT.ai Corporation, 2022. Computer Vision Annotation Tool (CVAT).
da Silveira, F., Lermen, F.H., Amaral, F.G., 2021. An overview of agriculture 4.0 development: Systematic review of descriptions, technologies, barriers, advantages, and disadvantages. Comput. Electron. Agric. 189, 106405. https://doi.org/10.1016/j.compag.2021.106405
Dantzig, G.B., Ramser, J.H., 1959. The Truck Dispatching Problem. Manag. Sci. 6, 80–91. https://doi.org/10.1287/mnsc.6.1.80
Davies, A., 2004. Computational intermediation and the evolution of computation as a commodity. Appl. Econ. 36, 1131–1142. https://doi.org/10.1080/0003684042000247334
De Grave, C., Verrelst, J., Morcillo-Pallarés, P., Pipia, L., Rivera-Caicedo, J.P., Amin, E., Belda, S., Moreno, J., 2020. Quantifying vegetation biophysical variables from the Sentinel-3/FLEX tandem mission: Evaluation of the synergy of OLCI and FLORIS data sources. Remote Sens. Environ. 251, 112101. https://doi.org/10.1016/j.rse.2020.112101

de Jong, S., Baja, H., Tamminga, K., Valente, J., 2022. APPLE MOTS: Detection, Segmentation and Tracking of Homogeneous Objects Using MOTS. IEEE Robot. Autom. Lett. 7, 11418–11425. https://doi.org/10.1109/LRA.2022.3199026

Deng, H., Aifantis, K.E., 2023. Applications of Lithium Batteries, in: Rechargeable Ion Batteries. John Wiley & Sons, Ltd, pp. 83–103. https://doi.org/10.1002/9783527836703.ch4

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., Fei-Fei, L., 2009. ImageNet: A large-scale hierarchical image database, in: 2009 IEEE Conference on Computer Vision and Pattern Recognition. Presented at the 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255. https://doi.org/10.1109/CVPR.2009.5206848

Deng, R., Tao, M., Huang, X., Bangura, K., Jiang, Q., Jiang, Y., Qi, L., 2021. Automated Counting Grains on the Rice Panicle Based on Deep Learning Method. Sensors 21, 281. https://doi.org/10.3390/s21010281

Dias, P.A., Tabb, A., Medeiros, H., 2018. Multispecies Fruit Flower Detection Using a Refined Semantic Segmentation Network. IEEE Robot. Autom. Lett. 3, 3003–3010. https://doi.org/10.1109/LRA.2018.2849498

Dietzmann, C., Duan, Y., 2022. Artificial Intelligence for Managerial Information Processing and Decision-Making in the Era of Information Overload. Hawaii Int. Conf. Syst. Sci. 2022 HICSS-55.

Dorigo, M., Maniezzo, V., Colorni, A., 1996. Ant system: optimization by a colony of cooperating agents. IEEE Trans. Syst. Man Cybern. Part B Cybern. 26, 29–41. https://doi.org/10.1109/3477.484436

Du, Y., Zhao, Z., Song, Y., Zhao, Y., Su, F., Gong, T., Meng, H., 2023. StrongSORT: Make DeepSORT Great Again. IEEE Trans. Multimed. 25, 8725–8737. https://doi.org/10.1109/TMM.2023.3240881

Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. Int. J. Inf. Manag. 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dunlap, A., Riquito, M., 2023. Social warfare for lithium extraction? Open-pit lithium mining, counterinsurgency tactics and enforcing green extractivism in northern Portugal. Energy Res. Soc. Sci. 95, 102912. https://doi.org/10.1016/j.erss.2022.102912

Durai, S.K.S., Shamili, M.D., 2022. Smart farming using Machine Learning and Deep Learning techniques. Decis. Anal. J. 3, 100041. https://doi.org/10.1016/j.dajour.2022.100041

Dwivedi, R., Dey, S., Chakraborty, C., Tiwari, S., 2021. Grape Disease Detection Network Based on Multi-Task Learning and Attention Features. IEEE Sens. J. 21, 17573–17580. https://doi.org/10.1109/JSEN.2021.3064060

Dyrmann, M., Jørgensen, R.N., Midtiby, H.S., 2017. RoboWeedSupport - Detection of weed locations in leaf occluded cereal crops using a fully convolutional neural network. Adv. Anim. Biosci. 8, 842–847. https://doi.org/10.1017/S2040470017000206

Dyrmann, M., Karstoft, H., Midtiby, H.S., 2016. Plant species classification using deep convolutional neural network. Biosyst. Eng. 151, 72–80. https://doi.org/10.1016/j.biosystemseng.2016.08.024

Edan, Y., Adamides, G., Oberti, R., 2023. Agriculture Automation, in: Nof, S.Y. (Ed.), Springer Handbook of Automation. Springer International Publishing, Cham, pp. 1055–1078. https://doi.org/10.1007/978-3-030-96729-1_49

Egbue, O., 2012. Assessment of social impacts of lithium for electric vehicle batteries. Presented at the IISE Annual Conference Proceedings, pp. 1–7.

EL Amraoui, K., Lghoul, M., Ezzaki, A., Masmoudi, L., Hadri, M., Elbelrhiti, H., Simo, A.A., 2022. Avo-AirDB: An avocado UAV Database for agricultural image segmentation and classification. Data Brief 45, 108738. https://doi.org/10.1016/j.dib.2022.108738

El-gayar, M.M., Soliman, H., meky, N., 2013. A comparative study of image low level feature extraction algorithms. Egypt. Inform. J. 14, 175–181. https://doi.org/10.1016/j.eij.2013.06.003

Eltom, M., Winefield, C. s., Trought, M. c. t., 2014. Effect of pruning system, cane size and season on inflorescence primordia initiation and inflorescence architecture of Vitis vinifera L. Sauvignon Blanc. Aust. J. Grape Wine Res. 20, 459–464. https://doi.org/10.1111/ajgw.12097

Englot, B., Hover, F., 2011. Multi-goal feasible path planning using ant colony optimization, in: 2011 IEEE International Conference on Robotics and Automation. Presented at the 2011 IEEE International Conference on Robotics and Automation, pp. 2255–2260. https://doi.org/10.1109/ICRA.2011.5980555

Escolà, A., Peña, J.M., López-Granados, F., Rosell-Polo, J.R., De Castro, A.I., Gregorio, E., Jiménez-Brenes, F.M., Sanz, R., Sebé, F., Llorens, J., Torres-Sánchez, J., 2023. Mobile terrestrial laser scanner vs. UAV photogrammetry to estimate woody crop canopy parameters – Part 1: Methodology and comparison in vineyards. Comput. Electron. Agric. 212, 108109. https://doi.org/10.1016/j.compag.2023.108109

Espinoza, M.A.M., Le, C.Z., Raheja, A., Bhandari, S., 2020. Weed identification and removal using machine learning techniques and unmanned ground vehicles, in: Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping V. Presented at the Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping V, SPIE, pp. 109–118. https://doi.org/10.1117/12.2557625

Etienne, L., Franck, P., Lavigne, C., Papaïx, J., Tolle, P., Ostandie, N., Rusch, A., 2022. Pesticide use in vineyards is affected by semi-natural habitats and organic farming share in the landscape. Agric. Ecosyst. Environ. 333, 107967. https://doi.org/10.1016/j.agee.2022.107967

Everingham, M., Van Gool, L., Williams, C.K.I., Winn, J., Zisserman, A., 2010. The Pascal Visual Object Classes (VOC) Challenge. Int. J. Comput. Vis. 88, 303–338. https://doi.org/10.1007/s11263-009-0275-4

Faiçal, B.S., Freitas, H., Gomes, P.H., Mano, L.Y., Pessin, G., de Carvalho, A.C.P.L.F., Krishnamachari, B., Ueyama, J., 2017. An adaptive approach for UAV-based pesticide spraying in dynamic environments. Comput. Electron. Agric. 138, 210–223. https://doi.org/10.1016/j.compag.2017.04.011

Fedele, G., González-Domínguez, E., Delière, L., Díez-Navajas, A.M., Rossi, V., 2020. Consideration of Latent Infections Improves the Prediction of Botrytis Bunch Rot Severity in Vineyards. Plant Dis. 104, 1291–1297. https://doi.org/10.1094/PDIS-11-19-2309-RE

Feng, W., Li, B., Ouyang, W., 2022. Multi-Object Tracking with Multiple Cues and Switcher-Aware Classification, in: 2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA). Presented at the 2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA), pp. 1–10. https://doi.org/10.1109/DICTA56598.2022.10034575

Ferrer-Ferrer, M., Ruiz-Hidalgo, J., Gregorio, E., Vilaplana, V., Morros, J.-R., Gené-Mola, J., 2023. Simultaneous fruit detection and size estimation using multitask deep neural networks. Biosyst. Eng. 233, 63–75. https://doi.org/10.1016/j.biosystemseng.2023.07.010

Finco, A., Bentivoglio, D., Belletti, M., Chiaraluce, G., Fiorentini, M., Ledda, L., Orsini, R., 2023. Does Precision Technologies Adoption Contribute to the Economic and Agri-Environmental Sustainability of Mediterranean Wheat Production? An Italian Case Study. Agronomy 13, 1818. https://doi.org/10.3390/agronomy13071818

Fradi, H., Bracco, L., Canino, F., Dugelay, J.-L., 2018. Autonomous Person Detection and Tracking Framework Using Unmanned Aerial Vehicles (UAVs). Presented at the 26th European Signal Processing Conference (EUSIPCO), Rome, Italy. https://doi.org/10.23919/EUSIPCO.2018.8553010

Fraga, H., Malheiro, A.C., Moutinho-Pereira, J., Santos, J.A., 2012. An overview of climate change impacts on European viticulture. Food Energy Secur. 1, 94–110. https://doi.org/10.1002/fes3.14

Frampton, W.J., Dash, J., Watmough, G., Milton, E.J., 2013. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. ISPRS J. Photogramm. Remote Sens. 82, 83–92. https://doi.org/10.1016/j.isprsjprs.2013.04.007

Friedman, L., Netanyahu, N.S., Shoshany, M., 2013. Mean shift-based clustering of remotely sensed data with agricultural and land-cover applications. Int. J. Remote Sens. 34, 6037–6053. https://doi.org/10.1080/01431161.2013.793866

Fry, D.M., 1995. Reproductive effects in birds exposed to pesticides and industrial chemicals. Environ. Health Perspect. 103, 165–171. https://doi.org/10.1289/ehp.95103s7165

Fuentes, A., Yoon, S., Kim, S.C., Park, D.S., 2017. A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. Sensors 17, 2022. https://doi.org/10.3390/s17092022

Fuhrimann, S., Farnham, A., Staudacher, P., Atuhaire, A., Manfioletti, T., Niwagaba, C.B., Namirembe, S., Mugweri, J., Winkler, M.S., Portengen, L., Kromhout, H., Mora, A.M., 2021. Exposure to multiple pesticides and neurobehavioral outcomes among smallholder farmers in Uganda. Environ. Int. 152, 106477. https://doi.org/10.1016/j.envint.2021.106477

Fukuda, M., Okuno, T., Yuki, S., 2021. Central Object Segmentation by Deep Learning to Continuously Monitor Fruit Growth through RGB Images. Sensors 21, 6999. https://doi.org/10.3390/s21216999

Furbank, R.T., Jimenez-Berni, J.A., George-Jaeggli, B., Potgieter, A.B., Deery, D.M., 2019. Field crop phenomics: enabling breeding for radiation use efficiency and biomass in cereal crops. New Phytol. 223, 1714–1727. https://doi.org/10.1111/nph.15817

Gackstetter, D., von Bloh, M., Hannus, V., Meyer, S.T., Weisser, W., Luksch, C., Asseng, S., 2023. Autonomous field management – An enabler of sustainable future in agriculture. Agric. Syst. 206, 103607. https://doi.org/10.1016/j.agsy.2023.103607

Gallo, I., Rehman, A.U., Dehkordi, R.H., Landro, N., La Grassa, R., Boschetti, M., 2023. Deep Object detection of Crop Weeds: Performance of YOLOv7 on a Real Case Dataset from UAV Images. Remote Sens. 15, 539. https://doi.org/10.3390/rs15020539

Ganesh, P., Volle, K., Burks, T.F., Mehta, S.S., 2019. Deep Orange: Mask R-CNN based Orange Detection and Segmentation. IFAC-Pap. 52, 70–75. https://doi.org/10.1016/j.ifacol.2019.12.499

Gao, F., Fang, W., Sun, X., Wu, Z., Zhao, G., Li, G., Li, R., Fu, L., Zhang, Q., 2022. A novel apple fruit detection and counting methodology based on deep learning and trunk tracking in modern orchard. Comput. Electron. Agric. 197, 107000. https://doi.org/10.1016/j.compag.2022.107000

Garcia, M.A.P., Montiel, O., Castillo, O., Sepúlveda, R., Melin, P., 2009. Path planning for autonomous mobile robot navigation with ant colony optimization and fuzzy cost function evaluation. Appl. Soft Comput. 9, 1102–1110. https://doi.org/10.1016/j.asoc.2009.02.014

Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., Villena-Martinez, V., Martinez-Gonzalez, P., Garcia-Rodriguez, J., 2018. A survey on deep learning techniques for image and video semantic segmentation. Appl. Soft Comput. 70, 41–65. https://doi.org/10.1016/j.asoc.2018.05.018

Gasparetto, A., Boscariol, P., Lanzutti, A., Vidoni, R., 2015. Path planning and Trajectory Planning Algorithms: A General Overview, in: Carbone, G., Gomez-Bravo, F. (Eds.), Motion and Operation Planning of Robotic Systems: Background and Practical Approaches, Mechanisms and Machine Science. Springer International Publishing, Cham, pp. 3–27. https://doi.org/10.1007/978-3-319-14705-5_1

Gasso, V., Sørensen, C.A.G., Oudshoorn, F.W., Green, O., 2013. Controlled traffic farming: A review of the environmental impacts. Eur. J. Agron. 48, 66–73. https://doi.org/10.1016/j.eja.2013.02.002

Gatti, M., Garavani, A., Squeri, C., Diti, I., De Monte, A., Scotti, C., Poni, S., 2022. Effects of intra-vineyard variability and soil heterogeneity on vine performance, dry matter and nutrient partitioning. Precis. Agric. 23, 150–177. https://doi.org/10.1007/s11119-021-09831-w

Gautam, H., Singh, S., Prashad, H., Kumar, A., Choudhary, A., Kaur, H., Narayan, O.P., Lal, S.K., Mehta, S., 2023. Chapter 12 - Pesticide toxicity and their impact on plant growth, active constituents and productivity, in: Husen, A. (Ed.), Plants and Their Interaction to Environmental Pollution. Elsevier, pp. 231–252. https://doi.org/10.1016/B978-0-323-99978-6.00008-X

Ge, Y., Lin, S., Zhang, Y., Li, Z., Cheng, H., Dong, J., Shao, S., Zhang, J., Qi, X., Wu, Z., 2022. Tracking and Counting of Tomato at Different Growth Period Using an Improving YOLO-Deepsort Network for Inspection Robot. Machines 10, 489. https://doi.org/10.3390/machines10060489

Geiger, A., Lenz, P., Stiller, C., Urtasun, R., 2013. Vision meets robotics: The KITTI dataset. Int. J. Robot. Res. 32, 1231–1237. https://doi.org/10.1177/0278364913491297

Gené-Mola, J., Sanz-Cortiella, R., Rosell-Polo, J.R., Morros, J.-R., Ruiz-Hidalgo, J., Vilaplana, V., Gregorio, E., 2020. Fuji-SfM dataset: A collection of annotated images and point clouds for Fuji apple detection and location using structure-from-motion photogrammetry. Data Brief 30, 105591. https://doi.org/10.1016/j.dib.2020.105591

Ghosh, A., Chakraborty, D., Law, A., 2018. Artificial intelligence in Internet of things. CAAI Trans. Intell. Technol. 3, 208–218. https://doi.org/10.1049/trit.2018.1008

Giahi, M., Bergstrom, D.J., Singh, B., 2023. Computational fluid dynamics analysis of an agricultural spray in a crossflow. Biosyst. Eng. 230, 329–343. https://doi.org/10.1016/j.biosystemseng.2023.05.001

Giakoumoglou, N., Pechlivani, E.M., Sakelliou, A., Klaridopoulos, C., Frangakis, N., Tzovaras, D., 2023a. Deep learning-based multi-spectral identification of grey mould. Smart Agric. Technol. 4, 100174. https://doi.org/10.1016/j.atech.2023.100174

Giakoumoglou, N., Pechlivani, E.M., Tzovaras, D., 2023b. Generate-Paste-Blend-Detect: Synthetic dataset for object detection in the agriculture domain. Smart Agric. Technol. 5, 100258. https://doi.org/10.1016/j.atech.2023.100258

Girshick, R., 2015. Fast R-CNN. IEEE Int. Conf. Comput. Vis. ICCV 1440–1448.

Girshick, R., Donahue, J., Darrell, T., Malik, J., 2014. Rich feature hierarchies for accurate object detection and semantic segmentation, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society, pp. 580–587. https://doi.org/10.1109/CVPR.2014.81

Gobierno de España, 2024. Salario Mínimo Interprofesional (SMI): ¿qué es, cuánto sube y a quién beneficia? [WWW Document]. URL https://www.lamoncloa.gob.es/serviciosdeprensa/notasprensa/trabajo14/Paginas/2023/140223-salario-minimo-interprofesional.aspx (accessed 4.20.24).

Göhlich, H., 1984. The development of tractors and other agricultural vehicles. J. Agric. Eng. Res. 29, 3–16. https://doi.org/10.1016/0021-8634(84)90055-6

Gole, P., Bedi, P., Marwaha, S., Haque, Md.A., Deb, C.K., 2023. TrIncNet: a lightweight vision transformer network for identification of plant diseases. Front. Plant Sci. 14, 1221557. https://doi.org/10.3389/fpls.2023.1221557

Gong, B., Ergu, D., Cai, Y., Ma, B., 2021. Real-Time Detection for Wheat Head Applying Deep Neural Network. Sensors 21, 191. https://doi.org/10.3390/s21010191

Gongal, A., Silwal, A., Amatya, S., Karkee, M., Zhang, Q., Lewis, K., 2016. Apple crop-load estimation with over-the-row machine vision system. Comput. Electron. Agric. 120, 26–35. https://doi.org/10.1016/j.compag.2015.10.022

Gonzalez-de-Santos, P., Ribeiro, A., Fernandez-Quintanilla, C., Lopez-Granados, F., Brandstoetter, M., Tomic, S., Pedrazzi, S., Peruzzi, A., Pajares, G., Kaplanis, G., Perez-Ruiz, M., Valero, C., del Cerro, J., Vieri, M., Rabatel, G., Debilde, B., 2017. Fleets of robots for environmentally-safe pest control in agriculture. Precis. Agric. 18, 574–614. https://doi.org/10.1007/s11119-016-9476-3

González-Domínguez, E., Caffi, T., Ciliberti, N., Rossi, V., 2015. A Mechanistic Model of Botrytis cinerea on Grapevines That Includes Weather, Vine Growth Stage, and the Main Infection Pathways. PLOS ONE 10, e0140444. https://doi.org/10.1371/journal.pone.0140444

Gonzalez-Dugo, V., Lopez-Lopez, M., Espadafor, M., Orgaz, F., Testi, L., Zarco-Tejada, P., Lorite, I.J., Fereres, E., 2019. Transpiration from canopy temperature: Implications for the assessment of crop yield in almond orchards. Eur. J. Agron. 105, 78–85. https://doi.org/10.1016/j.eja.2019.01.010

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2020. Generative adversarial networks. Commun. ACM 63, 139–144. https://doi.org/10.1145/3422622

Google OR-Tools, 2023. OR-Tools [WWW Document]. Google Dev. URL https://developers.google.com/optimization?hl=es-419 (accessed 1.17.24).

Google Scholar [WWW Document], 2023. URL https://scholar.google.com/ (accessed 5.31.23).

Griffin, T.W., Shockley, J.M., Mark, T.B., 2018. Economics of Precision farming, in: Precision agriculture Basics. John Wiley & Sons, Ltd, pp. 221–230. https://doi.org/10.2134/precisionagbasics.2016.0098

Guadagna, P., Fernandes, M., Chen, F., Santamaria, A., Teng, T., Frioni, T., Caldwell, D.G., Poni, S., Semini, C., Gatti, M., 2023. Using deep learning for pruning region detection and plant organ segmentation in dormant spur-pruned grapevines. Precis. Agric. https://doi.org/10.1007/s11119-023-10006-y

Güldenring, R., van Evert, F.K., Nalpantidis, L., 2023. RumexWeeds: A grassland dataset for agricultural robotics. J. Field Robot. 40, 1639–1656. https://doi.org/10.1002/rob.22196

Guo, Y., Liu, C., Coombes, M., 2021. Spraying Coverage Path planning for Agriculture Unmanned Aerial Vehicles, in: 2021 26th International Conference on Automation and Computing (ICAC). Presented at the 2021 26th International Conference on

Automation and Computing (ICAC), pp. 1–6. https://doi.org/10.23919/ICAC50006.2021.9594271

Gutiérrez, S., Diago, M.P., Fernández-Novales, J., Tardaguila, J., 2018. Vineyard water status assessment using on-the-go thermal imaging and machine learning. PLOS ONE 13, e0192037. https://doi.org/10.1371/journal.pone.0192037

Haalck, L., Mangan, M., Wystrach, A., Clement, L., Webb, B., Risse, B., 2023. CATER: Combined Animal Tracking & Environment Reconstruction. Sci. Adv. 9, eadg2094. https://doi.org/10.1126/sciadv.adg2094

Hafeez, A., Husain, M.A., Singh, S.P., Chauhan, Anurag, Khan, Mohd.T., Kumar, N., Chauhan, Abhishek, Soni, S.K., 2023. Implementation of drone technology for farm monitoring & pesticide spraying: A review. Inf. Process. Agric. 10, 192–203. https://doi.org/10.1016/j.inpa.2022.02.002

Hafiz, A.M., Bhat, G.M., 2020. A survey on instance segmentation: state of the art. Int. J. Multimed. Inf. Retr. 9, 171–189. https://doi.org/10.1007/s13735-020-00195-x

Hall, F.R., Fox, R.D., 1996. The Reduction of Pesticide Drift, in: Pesticide Formulation and Adjuvant Technology. CRC Press.

Häni, N., Roy, P., Isler, V., 2020a. MinneApple: A Benchmark Dataset for Apple Detection and Segmentation 5, 852–858.

Häni, N., Roy, P., Isler, V., 2020b. A comparative study of fruit detection and counting methods for yield mapping in apple orchards. J. Field Robot. 37, 263–282. https://doi.org/10.1002/rob.21902

Hanif, A.S., Han, X., Yu, S.-H., 2022. Independent Control Spraying System for UAV-Based Precise Variable Sprayer: A Review. Drones 6, 383. https://doi.org/10.3390/drones6120383

Hasanuzzaman, M., Mohsin, S.M., Bhuyan, M.H.M.B., Bhuiyan, T.F., Anee, T.I., Masud, A.A.C., Nahar, K., 2020. Chapter 3 - Phytotoxicity, environmental and health hazards of herbicides: challenges and ways forward, in: Prasad, M.N.V. (Ed.), Agrochemicals Detection, Treatment and Remediation. Butterworth-Heinemann, pp. 55–99. https://doi.org/10.1016/B978-0-08-103017-2.00003-9

Hassaballah, M., Kenk, M.A., Muhammad, K., Minaee, S., 2021. Vehicle Detection and Tracking in Adverse Weather Using a Deep Learning Framework. IEEE Trans. Intell. Transp. Syst. 22, 4230–4242. https://doi.org/10.1109/TITS.2020.3014013

He, H., Qiao, Y., Li, X., Chen, C., Zhang, X., 2021. Optimization on multi-object tracking and segmentation in pigs' weight measurement. Comput. Electron. Agric. 186, 106190. https://doi.org/10.1016/j.compag.2021.106190

He, K., Gkioxari, G., Dollar, P., Girshick, R., 2017. Mask R-CNN. Presented at the Proceedings of the IEEE International Conference on Computer Vision, pp. 2961–2969.

He, L., Wu, F., Du, X., Zhang, G., 2022. Cascade-SORT: A robust fruit counting approach using multiple features cascade matching. Comput. Electron. Agric. 200, 107223. https://doi.org/10.1016/j.compag.2022.107223

Heffner, E.L., Sorrells, M.E., Jannink, J.-L., 2009. Genomic Selection for Crop Improvement. Crop Sci. 49, 1–12. https://doi.org/10.2135/cropsci2008.08.0512

Hesabi, Z.R., Tari, Z., Goscinski, A., Fahad, A., Khalil, I., Queiroz, C., 2015. Data Summarization Techniques for Big Data—A Survey, in: Khan, S.U., Zomaya, A.Y. (Eds.), Handbook on Data Centers. Springer, New York, NY, pp. 1109–1152. https://doi.org/10.1007/978-1-4939-2092-1_38

Hibbard, M., Lurie, S., 2013. The New Natural Resource Economy: Environment and Economy in Transitional Rural Communities. Soc. Nat. Resour. 26, 827–844. https://doi.org/10.1080/08941920.2012.720358

Hill, G.N., Beresford, R.M., Evans, K.J., 2019. Automated Analysis of Aggregated Datasets to Identify Climatic Predictors of Botrytis Bunch Rot in Wine Grapes. Phytopathology® 109, 84–95. https://doi.org/10.1094/PHYTO-10-17-0357-R

Hilz, E., Vermeer, A.W.P., 2013. Spray drift review: The extent to which a formulation can contribute to spray drift reduction. Crop Prot. 44, 75–83. https://doi.org/10.1016/j.cropro.2012.10.020

Hong, S., Zhan, W., Dong, T., She, J., Min, C., Huang, H., Sun, Y., 2022. A Recognition Method of Bactrocera minax (Diptera: Tephritidae) Grooming Behavior via a Multi-Object Tracking and Spatio-Temporal Feature Detection Model. J. Insect Behav. 35, 67–81. https://doi.org/10.1007/s10905-022-09802-7

Horn, B.K.P., Schunck, B.G., 1981. Determining optical flow. Artif. Intell. 17, 185–203. https://doi.org/10.1016/0004-3702(81)90024-2

Hou, S., Feng, Y., Wang, Z., 2017. VegFru: A Domain-Specific Dataset for Fine-Grained Visual Categorization, in: 2017 IEEE International Conference on Computer Vision (ICCV). Presented at the 2017 IEEE International Conference on Computer Vision (ICCV), Venice. https://doi.org/10.1109/ICCV.2017.66

Houtman, W., Siagkris-Lekkos, A., Bos, D.J.M., van den Heuvel, B.J.P., Boer, M. den, Elfring, J., van de Molengraft, M.J.G., 2021. Automated flower counting from partial detections: Multiple hypothesis tracking with a connected-flower plant model. Comput. Electron. Agric. 188, 106346. https://doi.org/10.1016/j.compag.2021.106346

HSE-URV, 2023. XAG R150 UGV Sprayer (39gal /150L) [WWW Document]. HSE-UAV. URL https://hse-uav.com/products/r150-autonomous-tractor (accessed 4.13.24).

Hsu, H.-K., Yao, C.-H., Tsai, Y.-H., Hung, W.-C., Tseng, H.-Y., Singh, M., Yang, M.-H., 2020. Progressive Domain Adaptation for Object detection. Presented at the Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 749–757.

Hu, N., Su, D., Wang, S., Nyamsuren, P., Qiao, Y., Jiang, Y., Cai, Y., 2022. LettuceTrack: Detection and tracking of lettuce for robotic precision spray in agriculture. Front. Plant Sci. 13.

Huang, X., Hu, Z., Qiao, Y., Sukkarieh, S., 2023. Deep Learning-Based Cow Tail Detection and Tracking for Precision Livestock Farming. IEEEASME Trans. Mechatron. 28, 1213–1221. https://doi.org/10.1109/TMECH.2022.3175377

Iberdrola, 2023. Ofertas Luz Plan Online - IBERDROLA [WWW Document]. Iberdrola. URL https://www.iberdrola.es/luz/ofertas-plan-online (accessed 3.18.24).

Ibericadron, 2023. DJI Agras T40 [WWW Document]. IbericaDron. URL https://www.ibericadron.com/tienda/dji/t40/dji-agras-t40/ (accessed 3.18.24).

Íñiguez, R., Palacios, F., Barrio, I., Hernández, I., Gutiérrez, S., Tardaguila, J., 2021. Impact of Leaf Occlusions on Yield Assessment by Computer Vision in Commercial Vineyards. Agronomy 11, 1003. https://doi.org/10.3390/agronomy11051003

International Organisation of Vine and Wine, 2021. State of the World Vitiviniculture Sector in 2020. Paris, France.

International Organisation of Vine and Wine, 2009. OIV Descriptor List for Grape Varieties and Vitis Species, 2nd ed. Paris, France.

Ishengoma, F.S., Rai, I.A., Said, R.N., 2021. Identification of maize leaves infected by fall armyworms using UAV-based imagery and convolutional neural networks. Comput. Electron. Agric. 184, 106124. https://doi.org/10.1016/j.compag.2021.106124

Jannink, J.-L., Lorenz, A.J., Iwata, H., 2010. Genomic selection in plant breeding: from theory to practice. Brief. Funct. Genomics 9, 166–177. https://doi.org/10.1093/bfgp/elq001

Jansson, J.K., Hofmockel, K.S., 2020. Soil microbiomes and climate change. Nat. Rev. Microbiol. 18, 35–46. https://doi.org/10.1038/s41579-019-0265-7

Jennings, A.L., Ordonez, R., Ceccarelli, N., 2008. An Ant Colony Optimization using training data applied to UAV way point path planning in wind, in: 2008 IEEE Swarm Intelligence Symposium. Presented at the 2008 IEEE Swarm Intelligence Symposium, pp. 1–8. https://doi.org/10.1109/SIS.2008.4668302

Jeon, C.-W., Kim, H.-J., Yun, C., Park, S.-J., Hwang, Y.B., Han, X., 2024. Autonomous paddy field puddling and leveling operations based on full-coverage path generation and tracking. Precis. Agric. 25, 235–256. https://doi.org/10.1007/s11119-023-10066-0

Jia, W., Tian, Y., Luo, R., Zhang, Z., Lian, J., Zheng, Y., 2020. Detection and segmentation of overlapped fruits based on optimized mask R-CNN application in apple harvesting robot. Comput. Electron. Agric. 172. https://doi.org/10.1016/j.compag.2020.105380

Jiang, J., Liu, H., Zhao, C., He, C., Ma, J., Cheng, T., Zhu, Y., Cao, W., Yao, X., 2022. Evaluation of Diverse Convolutional Neural Networks and Training Strategies for Wheat Leaf Disease Identification with Field-Acquired Photographs. Remote Sens. 14, 3446. https://doi.org/10.3390/rs14143446

Jiang, Y., Li, C., Paterson, A.H., Robertson, J.S., 2019. DeepSeedling: deep convolutional network and Kalman filter for plant seedling detection and counting in the field. Plant Methods 15, 141. https://doi.org/10.1186/s13007-019-0528-3

Junos, M.H., Mohd Khairuddin, A.S., Thannirmalai, S., Dahari, M., 2021. An optimized YOLO-based object detection model for crop harvesting system. IET Image Process. 15, 2112–2125. https://doi.org/10.1049/ipr2.12181

Kaggle, 2023. Kaggle: Your Machine Learning and Data Science Community [WWW Document]. URL https://www.kaggle.com/ (accessed 9.11.23).

Kalia, A., Gosal, S.K., 2011. Effect of pesticide application on soil microorganisms. Arch. Agron. Soil Sci. 57, 569–596. https://doi.org/10.1080/03650341003787582

Kalman, R.E., 1960. A New Approach to Linear Filtering and Prediction Problems. J. Basic Eng. 82, 35–45. https://doi.org/10.1115/1.3662552

Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: A survey. Comput. Electron. Agric. 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Kandilli, G.G., Atak, A., Doyğacı, Y., Candar, S., Söylemezoğlu, G., Yılmaz, E., 2022. Disease resistance and fruit quality characteristics of 12 Vitis spp. grown in a humid-like climate region. Int. J. Agric. Environ. Food Sci. 6, 457–470. https://doi.org/10.31015/jaefs.2022.3.16

Kang, H., Chen, C., 2020. Fast implementation of real-time fruit detection in apple orchards using deep learning. Comput. Electron. Agric. 168, 105108. https://doi.org/10.1016/j.compag.2019.105108

Karatzinis, G.D., Apostolidis, S.D., Kapoutsis, A.Ch., Panagiotopoulou, L., Boutalis, Y.S., Kosmatopoulos, E.B., 2020. Towards an Integrated Low-Cost Agricultural Monitoring System with Unmanned Aircraft System, in: 2020 International Conference on Unmanned Aircraft Systems (ICUAS). Presented at the 2020 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 1131–1138. https://doi.org/10.1109/ICUAS48674.2020.9213900

Katal, A., Wazid, M., Goudar, R.H., 2013. Big data: Issues, challenges, tools and Good practices. 2013 Sixth Int. Conf. Contemp. Comput. IC3 404–409. https://doi.org/10.1109/IC3.2013.6612229

Katimbo, A., Rudnick, D.R., DeJonge, K.C., Lo, T.H., Qiao, X., Franz, T.E., Nakabuye, H.N., Duan, J., 2022. Crop water stress index computation approaches and their sensitivity to soil water dynamics. Agric. Water Manag. 266, 107575. https://doi.org/10.1016/j.agwat.2022.107575

Katoch, S., Chauhan, S.S., Kumar, V., 2021. A review on genetic algorithm: past, present, and future. Multimed. Tools Appl. 80, 8091–8126. https://doi.org/10.1007/s11042-020-10139-6

Kaur, P., Harnal, S., Gautam, V., Singh, M.P., Singh, S.P., 2022. An approach for characterization of infected area in tomato leaf disease based on deep learning and object detection technique. Eng. Appl. Artif. Intell. 115, 105210. https://doi.org/10.1016/j.engappai.2022.105210

Kefauver, S.C., Vicente, R., Vergara-Díaz, O., Fernandez-Gallego, J.A., Kerfal, S., Lopez, A., Melichar, J.P.E., Serret Molins, M.D., Araus, J.L., 2017. Comparative UAV and Field Phenotyping to Assess Yield and Nitrogen Use Efficiency in Hybrid and Conventional Barley. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.01733

Keller, M., 2020. The Science of Grapevines, 3rd ed. Academic Press.

Kestur, R., Meduri, A., Narasipura, O., 2019. MangoNet: A deep semantic segmentation architecture for a method to detect and count mangoes in an open orchard. Eng. Appl. Artif. Intell. 77, 59–69. https://doi.org/10.1016/j.engappai.2018.09.011

Khairunissa, J., Wahjuni, S., Soesanto, I.R.H., Wulandari, W., 2021. Detecting Poultry Movement for Poultry Behavioral Analysis using The Multi-Object Tracking (MOT) Algorithm, in: 2021 8th International Conference on Computer and Communication Engineering (ICCCE). Presented at the 2021 8th International Conference on Computer and Communication Engineering (ICCCE), pp. 265–268. https://doi.org/10.1109/ICCCE50029.2021.9467144

Khan, S., AlSuwaidan, L., 2022. Agricultural monitoring system in video surveillance object detection using feature extraction and classification by deep learning techniques. Comput. Electr. Eng. 102, 108201. https://doi.org/10.1016/j.compeleceng.2022.108201

Khan, S., Tufail, M., Khan, M.T., Khan, Z.A., Anwar, S., 2021. Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer. Precis. Agric. 22, 1711–1727. https://doi.org/10.1007/s11119-021-09808-9

Kiefer, B., Ott, D., Zell, A., 2021. Leveraging Synthetic Data in Object detection on Unmanned Aerial Vehicles.

Kienbaum, L., Correa Abondano, M., Blas, R., Schmid, K., 2021. DeepCob: precise and high-throughput analysis of maize cob geometry using deep learning with an application in genebank phenomics. Plant Methods 17, 91. https://doi.org/10.1186/s13007-021-00787-6

Kierdorf, J., Weber, I., Kicherer, A., Zabawa, L., Drees, L., Roscher, R., 2022. Behind the Leaves: Estimation of Occluded Grapevine Berries With Conditional Generative Adversarial Networks. Front. Artif. Intell. 5.

Kim, J., Suh, Y., Lee, J., Chae, H., Ahn, H., Chung, Y., Park, D., 2022. EmbeddedPigCount: Pig Counting with Video Object detection and tracking on an Embedded Board. Sensors 22, 2689. https://doi.org/10.3390/s22072689

Kim, M., Kim, W., 2020. Top-down thermal tracking based on rotatable elliptical motion model for intelligent livestock breeding. Multimed. Syst. 26, 509–517. https://doi.org/10.1007/s00530-020-00658-5

Kingma, D.P., Ba, J., 2017. Adam: A Method for Stochastic Optimization. https://doi.org/10.48550/arXiv.1412.6980

Klein, J., Waller, R.E., Pirk, S., Pałubicki, W., Tester, M., Michels, D., 2023. Synthetic Data at Scale: A Paradigm to Efficiently Leverage Machine Learning in Agriculture. https://doi.org/10.2139/ssrn.4314564

Klingman, G.C., Noordhoff, L.J., 1961. Weed control: as a science. Weed Control Sci.

Knauer, U., Matros, A., Petrovic, T., Zanker, T., Scott, E.S., Seiffert, U., 2017. Improved classification accuracy of powdery mildew infection levels of wine grapes by spatial-spectral analysis of hyperspectral images. Plant Methods 13, 47. https://doi.org/10.1186/s13007-017-0198-y

Koirala, A., Walsh, K.B., Wang, Z., McCarthy, C., 2019. Deep learning – Method overview and review of use for fruit detection and yield estimation. Comput. Electron. Agric. 162, 219–234. https://doi.org/10.1016/j.compag.2019.04.017

Komyshev, E., Genaev, M., Afonnikov, D., 2017. Evaluation of the SeedCounter, A Mobile Application for Grain Phenotyping. Front. Plant Sci. 7.

Koonce, B., 2021. EfficientNet, in: Koonce, B. (Ed.), Convolutional Neural Networks with Swift for Tensorflow: Image Recognition and Dataset Categorization. Apress, Berkeley, CA, pp. 109–123. https://doi.org/10.1007/978-1-4842-6168-2_10

Kragh, M.F., Christiansen, P., Laursen, M.S., Larsen, M., Steen, K.A., Green, O., Karstoft, H., Jørgensen, R.N., 2017. FieldSAFE: Dataset for Obstacle Detection in Agriculture. Sensors 17, 2579. https://doi.org/10.3390/s17112579

Krüger, S., Hanisch, C., Kwade, A., Winter, M., Nowak, S., 2014. Effect of impurities caused by a recycling process on the electrochemical performance of Li[Ni0.33Co0.33Mn0.33]O2. J. Electroanal. Chem. 726, 91–96. https://doi.org/10.1016/j.jelechem.2014.05.017

Kumar, D., Kukreja, V., 2021. N-CNN Based Transfer Learning Method for Classification of Powdery Mildew Wheat Disease, in: 2021 International Conference on Emerging Smart Computing and Informatics (ESCI). Presented at the 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), pp. 707–710. https://doi.org/10.1109/ESCI50559.2021.9396972

Kumar, K., Kumar, N., 2023. Region coverage-aware path planning for unmanned aerial vehicles: A systematic review. Phys. Commun. 59, 102073. https://doi.org/10.1016/j.phycom.2023.102073

Kumar, N., 2006. Breeding of Horticultural Crops: Principles and Practices. New India Publishing.

Kumar, Suneel, Röder, M.S., Singh, R.P., Kumar, Sundeep, Chand, R., Joshi, A.K., Kumar, U., 2016. Mapping of spot blotch disease resistance using NDVI as a substitute to visual observation in wheat (Triticum aestivum L.). Mol. Breed. 36, 95. https://doi.org/10.1007/s11032-016-0515-6

Kuska, M.T., Behmann, J., Großkinsky, D.K., Roitsch, T., Mahlein, A.-K., 2018. Screening of Barley Resistance Against Powdery Mildew by Simultaneous High-Throughput Enzyme Activity Signature Profiling and Multispectral Imaging. Front. Plant Sci. 9.

Kuska, M.T., Mahlein, A.-K., 2018. Aiming at decision making in plant disease protection and phenotyping by the use of optical sensors. Eur. J. Plant Pathol. 152, 987–992. https://doi.org/10.1007/s10658-018-1464-1

Lac, L., Da Costa, J.-P., Donias, M., Keresztes, B., Bardet, A., 2022. Crop stem detection and tracking for precision hoeing using deep learning. Comput. Electron. Agric. 192, 106606. https://doi.org/10.1016/j.compag.2021.106606

Lacerda, L.N., Snider, J., Cohen, Y., Liakos, V., Levi, M.R., Vellidis, G., 2022. Correlation of UAV and satellite-derived vegetation indices with cotton physiological parameters and their use as a tool for scheduling variable rate irrigation in cotton. Precis. Agric. 23, 2089–2114. https://doi.org/10.1007/s11119-022-09948-6

Lacotte, V., Peignier, S., Raynal, M., Demeaux, I., Delmotte, F., da Silva, P., 2022. Spatial–Spectral Analysis of Hyperspectral Images Reveals Early Detection of Downy Mildew on Grapevine Leaves. Int. J. Mol. Sci. 23, 10012. https://doi.org/10.3390/ijms231710012

Lagnelöv, O., Larsson, G., Nilsson, D., Larsolle, A., Hansson, P.-A., 2020. Performance comparison of charging systems for autonomous electric field tractors using dynamic simulation. Biosyst. Eng. 194, 121–137. https://doi.org/10.1016/j.biosystemseng.2020.03.017

Lal, R., 2016. Soil health and carbon management. Food Energy Secur. 5, 212–222. https://doi.org/10.1002/fes3.96

Lal, R., 2004. Carbon emission from farm operations. Environ. Int. 30, 981–990. https://doi.org/10.1016/j.envint.2004.03.005

Leal-Taixé, L., Milan, A., Reid, I., Roth, S., Schindler, K., 2015. MOTChallenge 2015: Towards a Benchmark for Multi-Target Tracking. https://doi.org/10.48550/arXiv.1504.01942

Lechenet, M., Bretagnolle, V., Bockstaller, C., Boissinot, F., Petit, M.-S., Petit, S., Munier-Jolain, N.M., 2014. Reconciling Pesticide Reduction with Economic and Environmental Sustainability in Arable Farming. PLOS ONE 9, e97922. https://doi.org/10.1371/journal.pone.0097922

LeCun, Y., Bengio, Y., 1995. Convolutional Networks for Images, Speech, and Time-Series, in: The Handbook of Brain Theory and Neural Networks, 3361. Presented at the The Handbook of Brain Theory and Neural Networks.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539

Lee, B.Y., Liew, L.H., Cheah, W.S., Wang, Y.C., 2014. Occlusion handling in videos object tracking: A survey. IOP Conf. Ser. Earth Environ. Sci. 18, 012020. https://doi.org/10.1088/1755-1315/18/1/012020

Leibe, B., Schindler, K., Van Gool, L., 2007. Coupled Detection and Trajectory Estimation for Multi-Object Tracking, in: 2007 IEEE 11th International Conference on Computer Vision. Presented at the 2007 IEEE 11th International Conference on Computer Vision, pp. 1–8. https://doi.org/10.1109/ICCV.2007.4408936

Li, D., Su, H., Jiang, K., Liu, D., Duan, X., 2022. Fish Face Identification Based on Rotated Object detection: Dataset and Exploration. Fishes 7, 219. https://doi.org/10.3390/fishes7050219

Li, G., Hui, X., Chen, Z., Chesser, G.D., Zhao, Y., 2021. Development and evaluation of a method to detect broilers continuously walking around feeder as an indication of restricted feeding behaviors. Comput. Electron. Agric. 181, 105982. https://doi.org/10.1016/j.compag.2020.105982

Li, J., Li, C., Fei, S., Ma, C., Chen, W., Ding, F., Wang, Y., Li, Y., Shi, J., Xiao, Z., 2021. Wheat Ear Recognition Based on RetinaNet and Transfer Learning. Sensors 21, 4845. https://doi.org/10.3390/s21144845

Li, J., Sheng, H., Zhang, J., Zhang, H., 2023. Coverage Path planning Method for Agricultural Spraying UAV in Arbitrary Polygon Area. Aerospace 10, 755. https://doi.org/10.3390/aerospace10090755

Li, K., Ge, F., Han, Y., Wang, Y., Xu, W., 2020. Path planning of multiple UAVs with online changing tasks by an ORPFOA algorithm. Eng. Appl. Artif. Intell. 94, 103807. https://doi.org/10.1016/j.engappai.2020.103807

Li, M., Zhang, Z., Lei, L., Wang, X., Guo, X., 2020. Agricultural Greenhouses Detection in High-Resolution Satellite Images Based on Convolutional Neural Networks: Comparison of Faster R-CNN, YOLO v3 and SSD. Sensors 20, 4938. https://doi.org/10.3390/s20174938

Li, R., Wang, R., Zhang, J., Xie, C., Liu, L., Wang, F., Chen, H., Chen, T., Hu, H., Jia, X., Hu, M., Zhou, M., Li, D., Liu, W., 2019. An Effective Data Augmentation Strategy for CNN-Based Pest Localization and Recognition in the Field. IEEE Access 7, 160274–160283. https://doi.org/10.1109/ACCESS.2019.2949852

Li, S., Yan, Z., Guo, Y., Su, X., Cao, Y., Jiang, B., Yang, F., Zhang, Z., Xin, D., Chen, Q., Zhu, R., 2022. SPM-IS: An auto-algorithm to acquire a mature soybean phenotype based on instance segmentation. Crop J., Crop phenotyping studies with application to crop monitoring 10, 1412–1423. https://doi.org/10.1016/j.cj.2021.05.014

Li, T., Feng, Q., Qiu, Q., Xie, F., Zhao, C., 2022. Occluded Apple Fruit Detection and Localization with a Frustum-Based Point-Cloud-Processing Approach for Robotic Harvesting. Remote Sens. 14, 482. https://doi.org/10.3390/rs14030482

Li, X., Zhao, Z., Wu, J., Huang, Y., Wen, J., Sun, S., Xie, H., Sun, J., Gao, Y., 2022. Y-BGD: Broiler counting based on multi-object tracking. Comput. Electron. Agric. 202, 107347. https://doi.org/10.1016/j.compag.2022.107347

Li, Yajun, Feng, Q., Liu, C., Xiong, Z., Sun, Y., Xie, F., Li, T., Zhao, C., 2023. MTA-YOLACT: Multitask-aware network on fruit bunch identification for cherry tomato robotic harvesting. Eur. J. Agron. 146, 126812. https://doi.org/10.1016/j.eja.2023.126812

Li, Yang, Ma, R., Zhang, R., Cheng, Y., Dong, C., 2023. A Tea Buds Counting Method Based on YOLOv5 and Kalman Filter Tracking Algorithm. Plant Phenomics 5. https://doi.org/10.34133/plantphenomics.0030

Li, Z., Guo, R., Li, M., Chen, Y., Li, G., 2020. A review of computer vision technologies for plant phenotyping. Comput. Electron. Agric. 176, 105672. https://doi.org/10.1016/j.compag.2020.105672

Liang, J., Huang, K., Lei, H., Zhong, Z., Cai, Y., Jiao, Z., 2024. Occlusion-aware fruit segmentation in complex natural environments under shape prior. Comput. Electron. Agric. 217, 108620. https://doi.org/10.1016/j.compag.2024.108620

Lin, D.J., Johnson, P.M., Knoll, F., Lui, Y.W., 2021. Artificial Intelligence for MR Image Reconstruction: An Overview for Clinicians. J. Magn. Reson. Imaging 53, 1015–1028. https://doi.org/10.1002/jmri.27078

Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C.L., Dolí, P., 2014. Microsoft COCO: Common Objects in Context, in: Computer Vision – ECCV 2014. ECCV 2014. Lecture Notes in Computer Science, Vol 8693. Springer, Cham. pp. 740–755. https://doi.org/10.1007/978-3-319-10602-1_48

Lin, Z., Mu, S., Huang, F., Mateen, K.A., Wang, M., Gao, W., Jia, J., 2019. A Unified Matrix-Based Convolutional Neural Network for Fine-Grained Image Classification of Wheat Leaf Diseases. IEEE Access 7, 11570–11590. https://doi.org/10.1109/ACCESS.2019.2891739

Liu, J., Xiang, J., Jin, Y., Liu, R., Yan, J., Wang, L., 2021. Boost Precision agriculture with Unmanned Aerial Vehicle Remote Sensing and Edge Intelligence: A Survey. Remote Sens. 13, 4387. https://doi.org/10.3390/rs13214387

Liu, L., Liang, J., Wang, J., Hu, P., Wan, L., Zheng, Q., 2023. An improved YOLOv5-based approach to soybean phenotype information perception. Comput. Electr. Eng. 106, 108582. https://doi.org/10.1016/j.compeleceng.2023.108582

Liu, L., Wang, R., Xie, C., Li, R., Wang, F., Qi, L., 2022. A global activated feature pyramid network for tiny pest detection in the wild. Mach. Vis. Appl. 33, 76. https://doi.org/10.1007/s00138-022-01310-0

Liu, S., Whitty, M., 2015. Automatic grape bunch detection in vineyards with an SVM classifier. J. Appl. Log. 13, 643–653. https://doi.org/10.1016/j.jal.2015.06.001

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., Berg, A.C., 2016. SSD: Single Shot MultiBox Detector, in: Leibe, B., Matas, J., Sebe, N., Welling, M. (Eds.), Computer Vision – ECCV 2016, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 21–37. https://doi.org/10.1007/978-3-319-46448-0_2

Liu, X., Chen, S.W., Aditya, S., Sivakumar, N., Dcunha, S., Qu, C., Taylor, C.J., Das, J., Kumar, V., 2018. Robust Fruit Counting: Combining Deep Learning, Tracking, and Structure from Motion. https://doi.org/10.48550/arXiv.1804.00307

Long, J., Shelhamer, E., Darrell, T., 2015. Fully Convolutional Networks for Semantic Segmentation. https://doi.org/10.48550/arXiv.1411.4038

Lowenberg-DeBoer, J. 1, Huang, I.Y. 2, Vasileios 1, G., Blackmore, S. 1 1 H.A.U., 2020. Economics of robots and automation in field crop production 278–299. https://doi.org/10.1007/s11119-019-09667-5

Loy, G., Zelinsky, A., 2003. Fast radial symmetry for detecting points of interest. IEEE Trans. Pattern Anal. Mach. Intell. 25, 959–973. https://doi.org/10.1109/TPAMI.2003.1217601

Lu, J., Lee, W.S., Gan, H., Hu, X., 2018. Immature citrus fruit detection based on local binary pattern feature and hierarchical contour analysis. Biosyst. Eng. 171, 78–90. https://doi.org/10.1016/j.biosystemseng.2018.04.009

Lu, Y., Chen, D., Olaniyi, E., Huang, Y., 2022. Generative adversarial networks (GANs) for image augmentation in agriculture: A systematic review. Comput. Electron. Agric. 200, 107208. https://doi.org/10.1016/j.compag.2022.107208

Luna, M.A., Ale Isaac, M.S., Ragab, A.R., Campoy, P., Flores Peña, P., Molina, M., 2022. Fast Multi-UAV Path planning for Optimal Area Coverage in Aerial Sensing Applications. Sensors 22, 2297. https://doi.org/10.3390/s22062297

Luo, C., Alarabi, S., Bi, Z., Jan, G.E., 2019. A Max-Min Ant System Approach to Autonomous Navigation, in: 2019 IEEE Congress on Evolutionary Computation (CEC). Presented at the 2019 IEEE Congress on Evolutionary Computation (CEC), pp. 1982–1987. https://doi.org/10.1109/CEC.2019.8790076

Lyu, S., Li, R., Zhao, Y., Li, Z., Fan, R., Liu, S., 2022. Green Citrus Detection and Counting in Orchards Based on YOLOv5-CS and AI Edge System. Sensors 22, 576. https://doi.org/10.3390/s22020576

Magalhães, S.C., dos Santos, F.N., Machado, P., Moreira, A.P., Dias, J., 2023. Benchmarking edge computing devices for grape bunches and trunks detection using accelerated object detection single shot multibox deep learning models. Eng. Appl. Artif. Intell. 117, 105604. https://doi.org/10.1016/j.engappai.2022.105604

Maja, J.M., Polak, M., Burce, M.E., Barnes, E., 2021. CHAP: Cotton-Harvesting Autonomous Platform. AgriEngineering 3, 199–217. https://doi.org/10.3390/agriengineering3020013

Marinoudi, V., Sørensen, C.G., Pearson, S., Bochtis, D., 2019. Robotics and labour in agriculture. A context consideration. Biosyst. Eng. 184, 111–121. https://doi.org/10.1016/j.biosystemseng.2019.06.013

Martinez-Guanter, J., Agüera, P., Agüera, J., Pérez-Ruiz, M., 2020. Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards. Precis. Agric. 21, 226–243. https://doi.org/10.1007/s11119-019-09665-7

Martínez-Peña, R., Vélez, S., Vacas, R., Martín, H., Álvarez, S., 2023a. Remote Sensing for Sustainable Pistachio Cultivation and Improved Quality Traits Evaluation through Thermal and Non-Thermal UAV Vegetation Indices. Appl. Sci. 13, 7716. https://doi.org/10.3390/app13137716

Martínez-Peña, R., Vergara-Díaz, O., Schlereth, A., Höhne, M., Morcuende, R., Nieto-Taladriz, M.T., Araus, J.L., Aparicio, N., Vicente, R., 2023b. Analysis of durum wheat photosynthetic organs during grain filling reveals the ear as a water stress-tolerant organ and the peduncle as the largest pool of primary metabolites. Planta 257, 81. https://doi.org/10.1007/s00425-023-04115-1

Martos, V., Ahmad, A., Cartujo, P., Ordoñez, J., 2021. Ensuring Agricultural Sustainability through Remote Sensing in the Era of Agriculture 5.0. Appl. Sci. 11, 5911. https://doi.org/10.3390/app11135911

Maslekar, N.V., Kulkarni, K.P., Chakravarthy, A.K., 2020. Application of Unmanned Aerial Vehicles (UAVs) for Pest Surveillance, Monitoring and Management, in: Chakravarthy, A.K. (Ed.), Innovative Pest Management Approaches for the 21st Century: Harnessing Automated Unmanned Technologies. Springer, Singapore, pp. 27–45. https://doi.org/10.1007/978-981-15-0794-6_2

Matese, A., Di Gennaro, S.F., 2015. Technology in precision viticulture: a state of the art review. Int. J. Wine Res. 69. https://doi.org/10.2147/IJWR.S69405

Matese, A., Di Gennaro, S.F., Berton, A., 2017. Assessment of a canopy height model (CHM) in a vineyard using UAV-based multispectral imaging. Int. J. Remote Sens. 38, 2150–2160. https://doi.org/10.1080/01431161.2016.1226002

Matese, A., Di Gennaro, S.F., Orlandi, G., Gatti, M., Poni, S., 2022. Assessing Grapevine Biophysical Parameters From Unmanned Aerial Vehicles Hyperspectral Imagery. Front. Plant Sci. 13, 898722. https://doi.org/10.3389/fpls.2022.898722

Matese, A., Toscano, P., Di Gennaro, S.F., Genesio, L., Vaccari, F.P., Primicerio, J., Belli, C., Zaldei, A., Bianconi, R., Gioli, B., 2015. Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision viticulture. Remote Sens. 7, 2971–2990. https://doi.org/10.3390/rs70302971

Matthews, G., Bateman, R., Miller, P., 2014. Pesticide Application Methods. John Wiley & Sons.

Mazumder, M., Banbury, C., Yao, X., Karlaš, B., Rojas, W.G., Diamos, S., Diamos, G., He, L., Parrish, A., Kirk, H.R., Quaye, J., Rastogi, C., Kiela, D., Jurado, D., Kanter, D., Mosquera, R., Ciro, J., Aroyo, L., Acun, B., Chen, L., Raje, M.S., Bartolo, M., Eyuboglu, S., Ghorbani, A., Goodman, E., Inel, O., Kane, T., Kirkpatrick, C.R., Kuo, T.-S., Mueller, J., Thrush, T., Vanschoren, J., Warren, M., Williams, A., Yeung, S., Ardalani, N., Paritosh, P., Bat-Leah, L., Zhang, C., Zou, J., Wu, C.-J., Coleman, C., Ng, A., Mattson, P., Reddi, V.J., 2023. DataPerf: Benchmarks for Data-Centric AI Development. https://doi.org/10.48550/arXiv.2207.10062

Mier, G., Valente, J., De Bruin, S., 2023. Fields2Cover: An Open-Source Coverage Path planning Library for Unmanned Agricultural Vehicles. IEEE Robot. Autom. Lett. 8, 2166–2172. https://doi.org/10.1109/LRA.2023.3248439

Mignoni, M.E., Honorato, A., Kunst, R., Righi, R., Massuquetti, A., 2022. Soybean images dataset for caterpillar and Diabrotica speciosa pest detection and classification. Data Brief 40, 107756. https://doi.org/10.1016/j.dib.2021.107756

Milella, A., Marani, R., Petitti, A., Reina, G., 2019. In-field high throughput grapevine phenotyping with a consumer-grade depth camera. Comput. Electron. Agric. 156, 293–306. https://doi.org/10.1016/j.compag.2018.11.026

Mirbod, O., Choi, D., Heinemann, P.H., Marini, R.P., He, L., 2023. On-tree apple fruit size estimation using stereo vision with deep learning-based occlusion handling. Biosyst. Eng. 226, 27–42. https://doi.org/10.1016/j.biosystemseng.2022.12.008

Mishra, A., Harnal, S., Gautam, V., Tiwari, D.R., Upadhyay, S., 2022. Weed density estimation in soya bean crop using deep convolutional neural networks in smart agriculture. J. Plant Dis. Prot. 129. https://doi.org/10.1007/s41348-022-00595-7

Misra, A.K., 2014. Climate change and challenges of water and food security. Int. J. Sustain. Built Environ. 3, 153–165. https://doi.org/10.1016/j.ijsbe.2014.04.006

Mochida, K., Koda, S., Inoue, K., Hirayama, T., Tanaka, S., Nishii, R., Melgani, F., 2019. Computer vision-based phenotyping for improvement of plant productivity: a machine learning perspective. GigaScience 8, giy153. https://doi.org/10.1093/gigascience/giy153

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., Group, T.P., 2009. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLOS Med. 6, e1000097. https://doi.org/10.1371/journal.pmed.1000097

Mohsan, S.A.H., Khan, M.A., Noor, F., Ullah, I., Alsharif, M.H., 2022. Towards the Unmanned Aerial Vehicles (UAVs): A Comprehensive Review. Drones 6, 147. https://doi.org/10.3390/drones6060147

Mohsan, S.A.H., Othman, N.Q.H., Li, Y., Alsharif, M.H., Khan, M.A., 2023. Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends. Intell. Serv. Robot. 16, 109–137. https://doi.org/10.1007/s11370-022-00452-4

Mokrane, A., Braham, A.C., Cherki, B., 2019. UAV Coverage Path planning For Supporting Autonomous Fruit Counting Systems, in: 2019 International Conference on Applied Automation and Industrial Diagnostics (ICAAID). Presented at the 2019 International Conference on Applied Automation and Industrial Diagnostics (ICAAID), pp. 1–5. https://doi.org/10.1109/ICAAID.2019.8934989

Molenhuis, J.R., 2020. Budgeting Farm Machinery Costs.

Molitor, D., Baus, O., Hoffmann, L., Beyer, M., 2016. Meteorological conditions determine the thermal-temporal position of the annual Botrytis bunch rot epidemic on Vitis vinifera L. cv. Riesling grapes. OENO One 50. https://doi.org/10.20870/oeno-one.2016.50.4.36

Morales-Rodríguez, P.A., Cano Cano, E., Villena, J., López-Perales, J.A., 2022. A Comparison between Conventional Sprayers and New UAV Sprayers: A Study Case of Vineyards and Olives in Extremadura (Spain). Agronomy 12, 1307. https://doi.org/10.3390/agronomy12061307

Morrone, S., Dimauro, C., Gambella, F., Cappai, M.G., 2022. Industry 4.0 and Precision Livestock Farming (PLF): An up to Date Overview across Animal Productions. Sensors 22, 4319. https://doi.org/10.3390/s22124319

Mota-Delfin, C., López-Canteñs, G. de J., López-Cruz, I.L., Romantchik-Kriuchkova, E., Olguín-Rojas, J.C., 2022. Detection and Counting of Corn Plants in the Presence of Weeds with Convolutional Neural Networks. Remote Sens. 14, 4892. https://doi.org/10.3390/rs14194892

Mukhamediev, R.I., Yakunin, K., Aubakirov, M., Assanov, I., Kuchin, Y., Symagulov, A., Levashenko, V., Zaitseva, E., Sokolov, D., Amirgaliyev, Y., 2023. Coverage Path planning Optimization of Heterogeneous UAVs Group for Precision agriculture. IEEE Access 11, 5789–5803. https://doi.org/10.1109/ACCESS.2023.3235207

Mutka, A.M., Bart, R.S., 2015. Image-based phenotyping of plant disease symptoms. Front. Plant Sci. 5. https://doi.org/10.3389/fpls.2014.00734

Myat Noe, S., Zin, T.T., Tin, P., Kobayashi, I., 2023. Comparing State-of-the-Art Deep Learning Algorithms for the Automated Detection and Tracking of Black Cattle. Sensors 23, 532. https://doi.org/10.3390/s23010532

Mylonas, I., Stavrakoudis, D., Katsantonis, D., Korpetis, E., 2020. Chapter 1 - Better farming practices to combat climate change, in: Ozturk, M., Gul, A. (Eds.), Climate

Change and Food Security with Emphasis on Wheat. Academic Press, pp. 1–29. https://doi.org/10.1016/B978-0-12-819527-7.00001-7

Naeem, H., Ahmad, J., Tayyab, M., 2013. Real-time object detection and tracking, in: INMIC. Presented at the INMIC, Lahore, Pakistan. https://doi.org/10.1109/INMIC.2013.6731341

Nanavati, R.V., Meng, Y., Coombes, M., Liu, C., 2023. Generalized data-driven optimal path planning framework for uniform coverage missions using crop spraying UAVs. Precis. Agric. 24, 1497–1525. https://doi.org/10.1007/s11119-023-09999-3

Naranjo-Torres, J., Mora, M., Hernández-García, R., Barrientos, R.J., Fredes, C., Valenzuela, A., 2020. A Review of Convolutional Neural Network Applied to Fruit Image Processing. Appl. Sci. 10, 3443. https://doi.org/10.3390/app10103443

Nawaz, M.F., Bourrié, G., Trolard, F., 2013. Soil compaction impact and modelling. A review. Agron. Sustain. Dev. 33, 291–309. https://doi.org/10.1007/s13593-011-0071-8

Neethirajan, S., 2022. ChickTrack – A quantitative tracking tool for measuring chicken activity. Measurement 191, 110819. https://doi.org/10.1016/j.measurement.2022.110819

Neuhold, G., Ollmann, T., Bulò, S.R., Kontschieder, P., 2017. The Mapillary Vistas Dataset for Semantic Understanding of Street Scenes, in: 2017 IEEE International Conference on Computer Vision (ICCV). Presented at the 2017 IEEE International Conference on Computer Vision (ICCV), pp. 5000–5009. https://doi.org/10.1109/ICCV.2017.534

Neven, D., De Brabandere, B., Proesmans, M., Van Gool, L., 2019. Instance Segmentation by Jointly Optimizing Spatial Embeddings and Clustering Bandwidth. https://doi.org/10.48550/arXiv.1906.11109

Nexles EU, 2023. Serenade ASO, 1 litre, Bayer fungicide | Nexles Europe [WWW Document]. URL https://www.nexles.com/eu/bayer-fungicide-serenade-aso-1-litre.html (accessed 3.20.24).

Nguyen, A., Le, B., 2013. 3D Point Cloud Segmentation: A survey, in: 6th IEEE Conference on Robotics, Automation and Mechatronics (RAM). pp. 225–230.

Nguyen, D.C.H., Dandy, G.C., Maier, H.R., Ascough, J.C., 2016. Improved Ant Colony Optimization for Optimal Crop and Irrigation Water Allocation by Incorporating Domain Knowledge. J. Water Resour. Plan. Manag. 142, 04016025. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000662

Nilsback, M.-E., Zisserman, A., 2006. A Visual Vocabulary for Flower Classification, in: 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06). Presented at the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), New York, pp. 1447–1454. https://doi.org/10.1109/CVPR.2006.42

Noble, W.S., 2006. What is a support vector machine? Nat. Biotechnol. 24, 1565–1567. https://doi.org/10.1038/nbt1206-1565

Nolan, P., Paley, D.A., Kroeger, K., 2017. Multi-UAS path planning for non-uniform data collection in precision agriculture, in: 2017 IEEE Aerospace Conference. Presented at the 2017 IEEE Aerospace Conference, pp. 1–12. https://doi.org/10.1109/AERO.2017.7943794

Nunes, M.R., van Es, H.M., Schindelbeck, R., Ristow, A.J., Ryan, M., 2018. No-till and cropping system diversification improve soil health and crop yield. Geoderma 328, 30–43. https://doi.org/10.1016/j.geoderma.2018.04.031

Nuske, S., Achar, S., Bates, T., Narasimhan, S., Singh, S., 2011. Yield estimation in vineyards by visual grape detection. Presented at the IEEE International Conference on Intelligent Robots and Systems, pp. 2352–2358. https://doi.org/10.1109/IROS.2011.6095069

Nuske, S., Wilshusen, K., Achar, S., Yoder, L., Narasimhan, S., Singh, S., 2014. Automated Visual Yield Estimation in Vineyards. J. Field Robot. 31, 837–860. https://doi.org/10.1002/rob.21541

Oberti, R., Marchi, M., Tirelli, P., Calcante, A., Iriti, M., Borghese, A.N., 2014. Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity. Comput. Electron. Agric. 104, 1–8. https://doi.org/10.1016/j.compag.2014.03.001

Oerke, E.-C., 2006. Crop losses to pests. J. Agric. Sci. 144, 31–43. https://doi.org/10.1017/S0021859605005708

Official Journal of the European Union, 2019. Directive 2009/128/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for Community action to achieve the sustainable use of pesticides.

Oksanen, T., Visala, A., 2009. Coverage path planning algorithms for agricultural field machines. J. Field Robot. 26, 651–668. https://doi.org/10.1002/rob.20300

Oliveira, P.M., Zannini, E., Arendt, E.K., 2014. Cereal fungal infection, mycotoxins, and lactic acid bacteria mediated bioprotection: From crop farming to cereal products. Food Microbiol., V International Symposium on Sourdough - Cereal Fermentation for Future Foods, Helsinki 10-12 October 2012 37, 78–95. https://doi.org/10.1016/j.fm.2013.06.003

Olmedo, N.A., Barczyk, M., Zhang, H., Wilson, W., Lipsett, M.G., 2020. A UGV-based modular robotic manipulator for soil sampling and terramechanics investigations. J. Unmanned Veh. Syst. 8, 364–381. https://doi.org/10.1139/juvs-2020-0003

Omar, T., Nehdi, M.L., 2016. Data acquisition technologies for construction progress tracking. Autom. Constr. 70, 143–155. https://doi.org/10.1016/j.autcon.2016.06.016

Omotilewa, O.J., Ricker-Gilbert, J., Ainembabazi, J.H., 2019. Subsidies for Agricultural Technology Adoption: Evidence from a Randomized Experiment with Improved Grain Storage Bags in Uganda. Am. J. Agric. Econ. 101, 753–772. https://doi.org/10.1093/ajae/aay108

Osman, Y., Dennis, R., Elgazzar, K., 2021. Yield Estimation and Visualization Solution for Precision agriculture. Sensors 21, 6657. https://doi.org/10.3390/s21196657

Osmond, C.B., Winter, K., Ziegler, H., 1982. Functional Significance of Different Pathways of CO2 Fixation in Photosynthesis, in: Lange, O.L., Nobel, P.S., Osmond, C.B., Ziegler, H. (Eds.), Physiological Plant Ecology II. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 479–547. https://doi.org/10.1007/978-3-642-68150-9_16

Pádua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J.J., Peres, E., Morais, R., 2017. UAS, sensors, and data processing in agroforestry: a review towards practical applications. Int. J. Remote Sens. 38, 2349–2391. https://doi.org/10.1080/01431161.2017.1297548

Pal, S.K., Pramanik, A., Maiti, J., Mitra, P., 2021. Deep learning in multi-object detection and tracking: state of the art. Appl. Intell. 51, 6400–6429. https://doi.org/10.1007/s10489-021-02293-7

Palacios, F., 2021. Computer vision and artificial intelligence for yield components' assessment in digital viticulture. Visión por ordenador e inteligencia artificial para la evaluación de los componentes del rendimiento en la viticultura digital.

Palacios, F., Diago, M.P., Melo-Pinto, P., Tardaguila, J., 2023. Early yield prediction in different grapevine varieties using computer vision and machine learning. Precis. Agric. 24, 407–435. https://doi.org/10.1007/s11119-022-09950-y

Pang, Z., Li, Z., Wang, N., 2023. SimpleTrack: Understanding and Rethinking 3D Multi-object Tracking, in: Karlinsky, L., Michaeli, T., Nishino, K. (Eds.), Computer Vision – ECCV 2022 Workshops, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 680–696. https://doi.org/10.1007/978-3-031-25056-9_43

Paniagua, A., 2020. Smart Villages in Depopulated Areas, in: Patnaik, S., Sen, S., Mahmoud, M.S. (Eds.), Smart Village Technology: Concepts and Developments. Springer International Publishing, Cham, pp. 399–409. https://doi.org/10.1007/978-3-030-37794-6_20

Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., Fountas, S., 2024. Economic and environmental benefits of digital agricultural technologies in crop production: A review. Smart Agric. Technol. 8, 100441. https://doi.org/10.1016/j.atech.2024.100441

Parez, S., Dilshad, N., Alghamdi, N.S., Alanazi, T.M., Lee, J.W., 2023. Visual Intelligence in Precision agriculture: Exploring Plant Disease Detection via Efficient Vision Transformers. Sensors 23, 6949. https://doi.org/10.3390/s23156949

Parker, S.S., Clifford, M.J., Cohen, B.S., 2024. Potential impacts of proposed lithium extraction on biodiversity and conservation in the contiguous United States. Sci. Total Environ. 911, 168639. https://doi.org/10.1016/j.scitotenv.2023.168639

Parks, C.G., Santos, A. de S.E., Lerro, C.C., DellaValle, C.T., Ward, M.H., Alavanja, M.C., Berndt, S.I., Beane Freeman, L.E., Sandler, D.P., Hofmann, J.N., 2019. Lifetime Pesticide Use and Antinuclear Antibodies in Male Farmers From the Agricultural Health Study. Front. Immunol. 10. https://doi.org/10.3389/fimmu.2019.01476

Patinha, C., Durães, N., Dias, A.C., Pato, P., Fonseca, R., Janeiro, A., Barriga, F., Reis, A.P., Duarte, A., Ferreira da Silva, E., Sousa, A.J., Cachada, A., 2018. Long-term application of the organic and inorganic pesticides in vineyards: Environmental record of past use. Appl. Geochem., SI: ISEG 2016 88, 226–238. https://doi.org/10.1016/j.apgeochem.2017.05.014

Pavithra, A., Kalpana, G., Vigneswaran, T., 2023. Deep learning-based automated disease detection and classification model for precision agriculture. Soft Comput. https://doi.org/10.1007/s00500-023-07936-0

Pavlovic, M., Koumboulis, F.N., Tzamtzi, M.P., Rozman, C., 2008. Role of automation agents in agribusiness decision support systems. Agrociencia 42, 913–923.

Pedersen, S.M., Lind, K.M., 2017. Precision agriculture – From Mapping to Site-Specific Application, in: Pedersen, Søren Marcus, Lind, Kim Martin (Eds.), Precision agriculture: Technology and Economic Perspectives. Springer International Publishing, Cham, pp. 1–20. https://doi.org/10.1007/978-3-319-68715-5_1

Pereira, L.S., 2017. Water, Agriculture and Food: Challenges and Issues. Water Resour. Manag. 31, 2985–2999. https://doi.org/10.1007/s11269-017-1664-z

Pérez Ruiz, M., Upadhyaya, S., 2012. GNSS in Precision Agricultural Operations. Intech. https://doi.org/10.5772/50448

Perez-Carabaza, S., Besada-Portas, E., Lopez-Orozco, J.A., de la Cruz, J.M., 2018. Ant colony optimization for multi-UAV minimum time search in uncertain domains. Appl. Soft Comput. 62, 789–806. https://doi.org/10.1016/j.asoc.2017.09.009

Perria, R., Ciofini, A., Petrucci, W.A., D'Arcangelo, M.E.M., Valentini, P., Storchi, P., Carella, G., Pacetti, A., Mugnai, L., 2022. A Study on the Efficiency of Sustainable Wine Grape Vineyard Management Strategies. Agronomy 12, 392. https://doi.org/10.3390/agronomy12020392

Pezzementi, Z., Tabor, T., Hu, P., Chang, J.K., Ramanan, D., Wellington, C., Wisely Babu, B.P., Herman, H., 2018. Comparing apples and oranges: Off-road pedestrian detection on the National Robotics Engineering Center agricultural person-detection dataset. J. Field Robot. 35, 545–563. https://doi.org/10.1002/rob.21760

Pham, T.H., Ichalal, D., Mammar, S., 2020. Complete coverage path planning for pests-ridden in precision agriculture using UAV, in: 2020 IEEE International Conference on Networking, Sensing and Control (ICNSC). Presented at the 2020 IEEE International Conference on Networking, Sensing and Control (ICNSC), pp. 1–6. https://doi.org/10.1109/ICNSC48988.2020.9238122

Pithan, P.A., Ducati, J.R., Garrido, L.R., Arruda, D.C., Thum, A.B., Hoff, R., 2021. Spectral characterization of fungal diseases downy mildew, powdery mildew, black-foot and Petri disease on Vitis vinifera leaves. Int. J. Remote Sens. 42, 5680–5697. https://doi.org/10.1080/01431161.2021.1929542

Porikli, F., 2006. Achieving real-time object detection and tracking under extreme conditions. J. Real-Time Image Process. 1, 33–40. https://doi.org/10.1007/s11554-006-0011-z

Porikli, F., Yilmaz, A., 2012. Object detection and tracking, in: Shan, C., Porikli, F., Xiang, T., Gong, S. (Eds.), Video Analytics for Business Intelligence, Studies in Computational Intelligence. Springer, Berlin, Heidelberg, pp. 3–41. https://doi.org/10.1007/978-3-642-28598-1_1

Pratama, M.T., Kim, S., Ozawa, S., Ohkawa, T., Chona, Y., Tsuji, H., Murakami, N., 2020a. Deep Learning-based Object detection for Crop Monitoring in Soybean Fields, in: 2020 International Joint Conference on Neural Networks (IJCNN). Presented at the 2020 International Joint Conference on Neural Networks (IJCNN), pp. 1–7. https://doi.org/10.1109/IJCNN48605.2020.9207400

Pratama, M.T., Kim, S., Ozawa, S., Ohkawa, T., Chona, Y., Tsuji, H., Murakami, N., 2020b. Deep Learning-based Object detection for Crop Monitoring in Soybean Fields, in: 2020 International Joint Conference on Neural Networks (IJCNN). Presented at the 2020 International Joint Conference on Neural Networks (IJCNN), pp. 1–7. https://doi.org/10.1109/IJCNN48605.2020.9207400

Punn, N.S., Sonbhadra, S.K., Agarwal, S., Rai, G., 2021. Monitoring COVID-19 social distancing with person detection and tracking via fine-tuned YOLO v3 and Deepsort techniques. https://doi.org/10.48550/arXiv.2005.01385

Qi, L., Jiang, L., Liu, S., Shen, X., Jia, J., 2019. Amodal Instance Segmentation With KINS Dataset. Presented at the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 3014–3023.

Qiang, Z., Shi, F., 2022. Pest disease detection of Brassica chinensis in wide scenes via machine vision: method and deployment. J. Plant Dis. Prot. 129, 533–544. https://doi.org/10.1007/s41348-021-00562-8

Qiao, S., Zhu, Y., Adam, H., Yuille, A., Chen, L.-C., 2020. ViP-DeepLab: Learning Visual Perception with Depth-aware Video Panoptic Segmentation. https://doi.org/10.48550/arXiv.2012.05258

Qiao, Y., Valente, J., Su, D., Zhang, Z., He, D., 2022. Editorial: AI, sensors and robotics in plant phenotyping and precision agriculture. Front. Plant Sci. 13.

Qin, W.-C., Qiu, B.-J., Xue, X.-Y., Chen, C., Xu, Z.-F., Zhou, Q.-Q., 2016. Droplet deposition and control effect of insecticides sprayed with an unmanned aerial vehicle against plant hoppers. Crop Prot. 85, 79–88. https://doi.org/10.1016/j.cropro.2016.03.018

Qiu, Z., Zhao, N., Zhou, L., Wang, M., Yang, L., Fang, H., He, Y., Liu, Y., 2020. Vision-Based Moving Obstacle Detection and Tracking in Paddy Field Using Improved Yolov3 and Deep SORT. Sensors 20, 4082. https://doi.org/10.3390/s20154082

Raghunathan, T.E., 2021. Synthetic Data. Annu. Rev. Stat. Its Appl. 8, 129–140. https://doi.org/10.1146/annurev-statistics-040720-031848

Rahaman, Md.M., Chen, D., Gillani, Z., Klukas, C., Chen, M., 2015. Advanced phenotyping and phenotype data analysis for the study of plant growth and development. Front. Plant Sci. 6.
Rahmalia, D., 2018. Estimation of Exponential Smoothing Parameter on Pesticide Characteristic Forecast Using Ant Colony Optimization (ACO). Eksakta 18, 56–63. https://doi.org/10.20885/eksakta.vol18.iss1.art6
Rahmat, R.F., Gunawan, D., Faza, S., Ginting, K., Nababan, E.B., 2018. Early Identification of Leaf Stain Disease in Sugar Cane Plants Using Speeded-Up Method Robust Features, in: 2018 Third International Conference on Informatics and Computing (ICIC). Presented at the 2018 Third International Conference on Informatics and Computing (ICIC), pp. 1–6. https://doi.org/10.1109/IAC.2018.8780482
Rahnemoonfar, M., Sheppard, C., 2017. Deep Count: Fruit Counting Based on Deep Simulated Learning. Sensors 17, 905. https://doi.org/10.3390/s17040905
Raj, R., Kar, S., Nandan, R., Jagarlapudi, A., 2020. Precision agriculture and Unmanned Aerial Vehicles (UAVs), in: Avtar, R., Watanabe, T. (Eds.), Unmanned Aerial Vehicle: Applications in Agriculture and Environment. Springer International Publishing, Cham, pp. 7–23. https://doi.org/10.1007/978-3-030-27157-2_2
Rakotondrasoa, H.M., Bucher, M., Sinayskiy, I., 2023. Quantitative Comparison of Nearest Neighbor Search Algorithms. https://doi.org/10.48550/arXiv.2307.05235
Rani, S.V.J., Kumar, P.S., Priyadharsini, R., Srividya, S.J., Harshana, S., 2022. Automated weed detection system in smart farming for developing sustainable agriculture. Int. J. Environ. Sci. Technol. 19, 9083–9094. https://doi.org/10.1007/s13762-021-03606-6
Raptis, E.K., Krestenitis, M., Egglezos, K., Kypris, O., Ioannidis, K., Doitsidis, L., Kapoutsis, A.Ch., Vrochidis, S., Kompatsiaris, I., Kosmatopoulos, E.B., 2023. End-to-end Precision agriculture UAV-Based Functionalities Tailored to Field Characteristics. J. Intell. Robot. Syst. 107, 23. https://doi.org/10.1007/s10846-022-01761-7
Razo-Belman, R., Ozuna, C., 2023. Volatile Organic Compounds: A Review of Their Current Applications as Pest Biocontrol and Disease Management. Horticulturae 9, 441. https://doi.org/10.3390/horticulturae9040441
Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You only look once: Unified, real-time object detection, in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE Computer Society, pp. 779–788. https://doi.org/10.1109/CVPR.2016.91
Redmon, J., Farhadi, A., 2018. YOLOv3: An Incremental Improvement.
Redmon, J., Farhadi, A., 2017. YOLO9000: Better, faster, stronger, in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Institute of Electrical and Electronics Engineers Inc., pp. 6517–6525. https://doi.org/10.1109/CVPR.2017.690
Reich, J., Chatterton, S., Johnson, D., 2017. Temporal Dynamics of Botrytis cinerea and Sclerotinia sclerotiorum in Seed Alfalfa Fields of Southern Alberta, Canada. Plant Dis. 101, 331–343. https://doi.org/10.1094/PDIS-04-16-0492-RE
Rejeb, A., Abdollahi, A., Rejeb, K., Treiblmaier, H., 2022. Drones in agriculture: A review and bibliometric analysis. Comput. Electron. Agric. 198, 107017. https://doi.org/10.1016/j.compag.2022.107017
Ren, S., He, K., Girshick, R., Sun, J., 2015. Faster R-CNN: Towards Real-Time Object detection with Region Proposal Networks. IEEE Trans. Pattern Anal. Mach. Intell. 39, 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031
Repsol, 2023. Agrodiesel e+10: el gasóleo agrícola para tu tractor [WWW Document]. REPSOL. URL https://www.repsol.es/autonomos-y-empresas/soluciones/gasoleo/gasoleo-agricola/ (accessed 3.18.24).

Reynolds, A.G., 2015. Grapevine breeding programs for the wine industry: Traditional and molecular techniques, 1st ed. Woodhead Publishing.

Rezk, N.G., Attia, A.-F., El-Rashidy, M.A., El-Sayed, A., Hemdan, E.E.-D., 2022. An Efficient Plant Disease Recognition System Using Hybrid Convolutional Neural Networks (CNNs) and Conditional Random Fields (CRFs) for Smart IoT Applications in Agriculture. Int. J. Comput. Intell. Syst. 15, 65. https://doi.org/10.1007/s44196-022-00129-x

Ribeiro, T., Lima, A., Vasconcelos, C., 2021. The need for transparent communication in mining: a case study in lithium exploitation. Int. J. Sci. Educ. Part B 11, 324–343. https://doi.org/10.1080/21548455.2021.1999530

Ribeiro-Gomes, K., Hernandez-Lopez, D., Ballesteros, R., Moreno, M.A., 2016. Approximate georeferencing and automatic blurred image detection to reduce the costs of UAV use in environmental and agricultural applications. Biosyst. Eng. 151, 308–327. https://doi.org/10.1016/j.biosystemseng.2016.09.014

Rist, F., Gabriel, D., Mack, J., Steinhage, V., Töpfer, R., Herzog, K., 2019. Combination of an Automated 3D Field Phenotyping Workflow and Predictive Modelling for High-Throughput and Non-Invasive Phenotyping of Grape Bunches. Remote Sens. 11, 2953. https://doi.org/10.3390/rs11242953

Roboflow Universe, 2023. Roboflow Universe: Open Source Computer Vision Community [WWW Document]. Roboflow. URL https://universe.roboflow.com/ (accessed 9.11.23).

Rodríguez-Rajo, F.J., Jato, V., Fernández-González, M., Aira, M.J., 2010. The use of aerobiological methods for forecasting Botrytis spore concentrations in a vineyard. Grana 49, 56–65. https://doi.org/10.1080/00173130903472393

Rong, J., Zhou, H., Zhang, F., Yuan, T., Wang, P., 2023. Tomato cluster detection and counting using improved YOLOv5 based on RGB-D fusion. Comput. Electron. Agric. 207, 107741. https://doi.org/10.1016/j.compag.2023.107741

Rose, J.C., Kicherer, A., Wieland, M., Klingbeil, L., Töpfer, R., Kuhlmann, H., 2016. Towards Automated Large-Scale 3D Phenotyping of Vineyards under Field Conditions. Sensors 16, 2136. https://doi.org/10.3390/s16122136

Roure, F., Moreno, G., Soler, M., Faconti, D., Serrano, D., Astolfi, P., Bardaro, G., Gabrielli, A., Bascetta, L., Matteucci, M., 2018. GRAPE: Ground Robot for vineyArd Monitoring and ProtEction, in: Ollero, A., Sanfeliu, A., Montano, L., Lau, N., Cardeira, C. (Eds.), ROBOT 2017: Third Iberian Robotics Conference, Advances in Intelligent Systems and Computing. Springer International Publishing, Cham, pp. 249–260. https://doi.org/10.1007/978-3-319-70833-1_21

Roy, A.M., Bose, R., Bhaduri, J., 2022. A fast accurate fine-grain object detection model based on YOLOv4 deep neural network. Neural Comput. Appl. 34, 3895–3921. https://doi.org/10.1007/s00521-021-06651-x

Roy, T., George K, J., 2020. Precision farming: A Step Towards Sustainable, Climate-Smart Agriculture, in: Venkatramanan, V., Shah, S., Prasad, R. (Eds.), Global Climate Change: Resilient and Smart Agriculture. Springer, Singapore, pp. 199–220. https://doi.org/10.1007/978-981-32-9856-9_10

Sadeghi-Tehran, P., Virlet, N., Ampe, E.M., Reyns, P., Hawkesford, M.J., 2019. DeepCount: In-Field Automatic Quantification of Wheat Spikes Using Simple Linear Iterative Clustering and Deep Convolutional Neural Networks. Front. Plant Sci. 10.

Sadgrove, E.J., Falzon, G., Miron, D., Lamb, D., 2017. Fast object detection in pastoral landscapes using a Colour Feature Extreme Learning Machine. Comput. Electron. Agric. 139, 204–212. https://doi.org/10.1016/j.compag.2017.05.017

Sadgrove, E.J., Falzon, G., Miron, D., Lamb, D.W., 2018. Real-time object detection in agricultural/remote environments using the multiple-expert colour feature extreme learning machine (MEC-ELM). Comput. Ind. 98, 183–191. https://doi.org/10.1016/j.compind.2018.03.014

Sadik, M.A., Moussa, S., El-Sayed, A., Fayed, Z.T., 2022. Vehicles Detection and Tracking in Advanced & Automated Driving Systems: Limitations and Challenges. Int. J. Intell. Comput. Inf. Sci. 22, 54–69. https://doi.org/10.21608/ijicis.2022.117646.1158

Saiz-Rubio, V., Rovira-Más, F., 2020. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agronomy 10, 207. https://doi.org/10.3390/agronomy10020207

Salim, S., Khalifa, O.O., Rahman, F.A., Lajis, A., 2019. Crowd Detection And Tracking In Surveillance Video Sequences, in: 2019 IEEE International Conference on Smart Instrumentation, Measurement and Application (ICSIMA). Presented at the 2019 IEEE International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), pp. 1–6. https://doi.org/10.1109/ICSIMA47653.2019.9057300

Santos, C.F.G.D., Papa, J.P., 2022. Avoiding Overfitting: A Survey on Regularization Methods for Convolutional Neural Networks. ACM Comput. Surv. 54, 213:1-213:25. https://doi.org/10.1145/3510413

Santos, L.C., Aguiar, A.S., Santos, F.N., Valente, A., Ventura, J.B., Sousa, A.J., 2021. Navigation Stack for Robots Working in Steep Slope Vineyard, in: Arai, K., Kapoor, S., Bhatia, R. (Eds.), Intelligent Systems and Applications, Advances in Intelligent Systems and Computing. Springer International Publishing, London, UK, pp. 264–285. https://doi.org/10.1007/978-3-030-55180-3_21

Santos, L.C., Santos, F.N., Valente, A., Sobreira, H., Sarmento, J., Petry, M., 2022. Collision Avoidance Considering Iterative Bézier Based Approach for Steep Slope Terrains. IEEE Access 10, 25005–25015. https://doi.org/10.1109/ACCESS.2022.3153496

Santos, T., de Souza, L., Andreza, dos S., Avila, S., 2019. Embrapa Wine Grape Instance Segmentation Dataset – Embrapa WGISD. https://doi.org/10.5281/zenodo.3361736

Santos, T., de Souza, L.L., Santos, A.A. dos, Avila, S., 2020. Grape detection, segmentation and tracking using deep neural networks and three-dimensional association. Comput. Electron. Agric. 170, 105247. https://doi.org/10.1016/J.COMPAG.2020.105247

Santos, V. de C., Osório, F.S., Toledo, C.F.M., Otero, F.E.B., Johnson, C.G., 2016. Exploratory path planning using the Max-min ant system algorithm, in: 2016 IEEE Congress on Evolutionary Computation (CEC). Presented at the 2016 IEEE Congress on Evolutionary Computation (CEC), pp. 4229–4235. https://doi.org/10.1109/CEC.2016.7744327

Šarauskis, E., Kazlauskas, M., Naujokienė, V., Bručienė, I., Steponavičius, D., Romaneckas, K., Jasinskas, A., 2022. Variable Rate Seeding in Precision agriculture: Recent Advances and Future Perspectives. Agriculture 12, 305. https://doi.org/10.3390/agriculture12020305

Sardaro, R., La Sala, P., De Pascale, G., Faccilongo, N., 2021. The conservation of cultural heritage in rural areas: Stakeholder preferences regarding historical rural buildings in Apulia, southern Italy. Land Use Policy 109, 105662. https://doi.org/10.1016/j.landusepol.2021.105662

Saseendran, A.T., Setia, L., Chhabria, V., Chakraborty, D., Roy, A.B., 2019. Impact of Data Pruning on Machine Learning Algorithm Performance. https://doi.org/10.48550/arXiv.1901.10539

Schreefel, L., Schulte, R.P.O., de Boer, I.J.M., Schrijver, A.P., van Zanten, H.H.E., 2020. Regenerative agriculture – the soil is the base. Glob. Food Secur. 26, 100404. https://doi.org/10.1016/j.gfs.2020.100404

Schreiner, C., Torkkola, K., Gardner, M., Zhang, K., 2006. Using Machine Learning Techniques to Reduce Data Annotation Time. Proc. Hum. Factors Ergon. Soc. Annu. Meet. 50, 2438–2442. https://doi.org/10.1177/154193120605002219

ScienceDirect [WWW Document], 2023. URL https://www.sciencedirect.com/ (accessed 5.31.23).

Seelan, S.K., Laguette, S., Casady, G.M., Seielstad, G.A., 2003. Remote sensing applications for precision agriculture: A learning community approach. Remote Sens. Environ., IKONOS Fine Spatial Resolution Land Observation 88, 157–169. https://doi.org/10.1016/j.rse.2003.04.007

Seethepalli, A., Guo, H., Liu, X., Griffiths, M., Almtarfi, H., Li, Z., Liu, S., Zare, A., Fritschi, F.B., Blancaflor, E.B., Ma, X.-F., York, L.M., 2020. RhizoVision Crown: An Integrated Hardware and Software Platform for Root Crown Phenotyping. Plant Phenomics 2020. https://doi.org/10.34133/2020/3074916

Selim, S., Sonmez, N.K., Coslu, M., Onur, I., 2019. Semi-automatic Tree Detection from Images of Unmanned Aerial Vehicle Using Object-Based Image Analysis Method. J. Indian Soc. Remote Sens. 47, 193–200. https://doi.org/10.1007/s12524-018-0900-1

Seo, D., Cho, B.-H., Kim, K.-C., 2021. Development of Monitoring Robot System for Tomato Fruits in Hydroponic Greenhouses. Agronomy 11, 2211. https://doi.org/10.3390/agronomy11112211

Setten, G., 2006. Farming the Heritage: On the Production and Construction of a Personal and Practised Landscape Heritage, in: The Nature of Cultural Heritage, and the Culture of Natural Heritage. Routledge.

Shafiq, M., Ali, Z.A., Israr, A., Alkhammash, E.H., Hadjouni, M., Jussila, J.J., 2022. Convergence Analysis of Path planning of Multi-UAVs Using Max-Min Ant Colony Optimization Approach. Sensors 22, 5395. https://doi.org/10.3390/s22145395

Sheema, D., Ramesh, K., Renjith, P.N., Lakshna, A., 2021. Comparative Study of Major Algorithms for Pest Detection in Maize Crop, in: 2021 International Conference on Intelligent Technologies (CONIT). Presented at the 2021 International Conference on Intelligent Technologies (CONIT), pp. 1–7. https://doi.org/10.1109/CONIT51480.2021.9498280

Shefali, Kumar, Rahul, Sankhla, M.S., Kumar, Rajeev, Sonone, S.S., 2020. Impact of Pesticide Toxicity in Aquatic Environment.

Shen, L., Su, J., He, R., Song, L., Huang, R., Fang, Y., Song, Y., Su, B., 2023. Real-time tracking and counting of grape clusters in the field based on channel pruning with YOLOv5s. Comput. Electron. Agric. 206, 107662. https://doi.org/10.1016/j.compag.2023.107662

Shen, Y., Kong, W., Shi, R., Du, R., Zhao, M., 2023. Farmers' adoption behavior of conservation tillage technology: a multidimensional heterogeneity perspective. Environ. Sci. Pollut. Res. 30, 37744–37761. https://doi.org/10.1007/s11356-022-24716-9

Shi, M., Feng, X., Pan, S., Song, X., Jiang, L., 2023. A Collaborative Path planning Method for Intelligent Agricultural Machinery Based on Unmanned Aerial Vehicles. Electronics 12, 3232. https://doi.org/10.3390/electronics12153232

Shorten, C., Khoshgoftaar, T.M., 2019. A survey on Image Data Augmentation for Deep Learning. J. Big Data 6, 60. https://doi.org/10.1186/s40537-019-0197-0

Shruthi, U., Nagaveni, V., Raghavendra, B.K., 2019. A Review on Machine Learning Classification Techniques for Plant Disease Detection, in: 2019 5th International

Conference on Advanced Computing & Communication Systems (ICACCS). Presented at the 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), pp. 281–284. https://doi.org/10.1109/ICACCS.2019.8728415

Sibhatu, K.T., Qaim, M., 2017. Rural food security, subsistence agriculture, and seasonality. PLOS ONE 12, e0186406. https://doi.org/10.1371/journal.pone.0186406

Sidla, O., Lypetskyy, Y., Brandle, N., Seer, S., 2006. Pedestrian Detection and Tracking for Counting Applications in Crowded Situations, in: 2006 IEEE International Conference on Video and Signal Based Surveillance. Presented at the 2006 IEEE International Conference on Video and Signal Based Surveillance, pp. 70–70. https://doi.org/10.1109/AVSS.2006.91

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc. 1–14.

Singh, A., 2016. Optimal Allocation of Resources for Increasing Farm Revenue under Hydrological Uncertainty. Water Resour. Manag. 30, 2569–2580. https://doi.org/10.1007/s11269-016-1306-x

Singh, A., Arora, M., 2020. CNN Based Detection of Healthy and Unhealthy Wheat Crop, in: 2020 International Conference on Smart Electronics and Communication (ICOSEC). Presented at the 2020 International Conference on Smart Electronics and Communication (ICOSEC), pp. 121–125. https://doi.org/10.1109/ICOSEC49089.2020.9215340

Singh, A.P., Yerudkar, A., Mariani, V., Iannelli, L., Glielmo, L., 2022. A Bibliometric Review of the Use of Unmanned Aerial Vehicles in Precision agriculture and Precision viticulture for Sensing Applications. Remote Sens. 14, 1604. https://doi.org/10.3390/rs14071604

Singh, N.S., Sharma, R., Parween, T., Patanjali, P.K., 2018. Pesticide Contamination and Human Health Risk Factor, in: Oves, M., Zain Khan, M., M.I. Ismail, I. (Eds.), Modern Age Environmental Problems and Their Remediation. Springer International Publishing, Cham, pp. 49–68. https://doi.org/10.1007/978-3-319-64501-8_3

Singh, R., Wu, W., Wang, G., Kalra, M.K., 2020. Artificial intelligence in image reconstruction: The change is here. Phys. Med., 125 Years of X-Rays 79, 113–125. https://doi.org/10.1016/j.ejmp.2020.11.012

Siriani, A.L.R., Kodaira, V., Mehdizadeh, S.A., de Alencar Nääs, I., de Moura, D.J., Pereira, D.F., 2022. Detection and tracking of chickens in low-light images using YOLO network and Kalman filter. Neural Comput. Appl. 34, 21987–21997. https://doi.org/10.1007/s00521-022-07664-w

Sishodia, R.P., Ray, R.L., Singh, S.K., 2020. Applications of Remote Sensing in Precision agriculture: A Review. Remote Sens. 12, 3136. https://doi.org/10.3390/rs12193136

Snapp, S.S., Blackie, M.J., Donovan, C., 2003. Realigning research and extension to focus on farmers' constraints and opportunities. Food Policy, Special Issue on Input Use and Market Development in Sub-Saharan Africa 28, 349–363. https://doi.org/10.1016/j.foodpol.2003.08.002

Solis-Sánchez, L.O., Castañeda-Miranda, R., García-Escalante, J.J., Torres-Pacheco, I., Guevara-González, R.G., Castañeda-Miranda, C.L., Alaniz-Lumbreras, P.D., 2011. Scale invariant feature approach for insect monitoring. Comput. Electron. Agric. 75, 92–99. https://doi.org/10.1016/j.compag.2010.10.001

Song, P., Wang, J., Guo, X., Yang, W., Zhao, C., 2021. High-throughput phenotyping: Breaking through the bottleneck in future crop breeding. Crop J., Rice as a model crop: genetics, genomics and breeding 9, 633–645. https://doi.org/10.1016/j.cj.2021.03.015

Sophocleous, M., 2021. Towards Fully Automated Decision-Making Systems for Precision agriculture: Soil Sensing Technologies – "The Missing Link," in: Precision agriculture Technologies for Food Security and Sustainability. IGI Global, pp. 71–93. https://doi.org/10.4018/978-1-7998-5000-7.ch004

Springer [WWW Document], 2023. URL https://link.springer.com/ (accessed 5.31.23).

Stein, M., Bargoti, S., Underwood, J., 2016. Image Based Mango Fruit Detection, Localisation and Yield Estimation Using Multiple View Geometry. Sensors 16, 1915. https://doi.org/10.3390/s16111915

Storey, G., Meng, Q., Li, B., 2022. Leaf Disease Segmentation and Detection in Apple Orchards for Precise Smart Spraying in Sustainable Agriculture. Sustainability 14, 1458. https://doi.org/10.3390/su14031458

Stützle, T., 1999. Local search algorithms for combinatorial problems - analysis, improvements, and new applications. Presented at the DISKI.

Stützle, T., Dorigo, M., 2004. Ant Colony Optimization. Bradford Company, Massachussets.

Su, D., Kong, H., Qiao, Y., Sukkarieh, S., 2021. Data augmentation for deep learning based semantic segmentation and crop-weed classification in agricultural robotics. Comput. Electron. Agric. 190, 106418. https://doi.org/10.1016/j.compag.2021.106418

Su, W.-H., Zhang, J., Yang, C., Page, R., Szinyei, T., Hirsch, C.D., Steffenson, B.J., 2021. Automatic Evaluation of Wheat Resistance to Fusarium Head Blight Using Dual Mask-RCNN Deep Learning Frameworks in Computer Vision. Remote Sens. 13, 26. https://doi.org/10.3390/rs13010026

Sudars, K., Jasko, J., Namatevs, I., Ozola, L., Badaukis, N., 2020. Dataset of annotated food crops and weed images for robotic computer vision control. Data Brief 31, 105833. https://doi.org/10.1016/j.dib.2020.105833

Sun, S., Song, H., He, D., Long, Y., 2019. An adaptive segmentation method combining MSRCR and mean shift algorithm with K-means correction of green apples in natural environment. Inf. Process. Agric. 6, 200–215. https://doi.org/10.1016/j.inpa.2018.08.011

Talukdar, J., Gupta, S., Rajpura, P., Hegde, R., 2018. Transfer Learning for Object detection using State-of-the-Art Deep Neural Networks. https://doi.org/10.1109/SPIN.2018.8474198

Tan, C., Li, C., He, D., Song, H., 2022. Towards real-time tracking and counting of seedlings with a one-stage detector and optical flow. Comput. Electron. Agric. 193, 106683. https://doi.org/10.1016/j.compag.2021.106683

Tan, S., Lu, H., Yu, J., Lan, M., Hu, X., Zheng, H., Peng, Y., Wang, Y., Li, Z., Qi, L., Ma, X., 2023. In-field rice panicles detection and growth stages recognition based on RiceRes2Net. Comput. Electron. Agric. 206, 107704. https://doi.org/10.1016/j.compag.2023.107704

Tang, S., Andriluka, M., Schiele, B., 2014. Detection and Tracking of Occluded People. Int. J. Comput. Vis. 110, 58–69. https://doi.org/10.1007/s11263-013-0664-6

Tang, S., Tang, G., Cheke, R.A., 2010. Optimum timing for integrated pest management: Modelling rates of pesticide application and natural enemy releases. J. Theor. Biol. 264, 623–638. https://doi.org/10.1016/j.jtbi.2010.02.034

Taylor, J., 2004. Precision viticulture and Digital Terroir: Investigations into the application of information technology in Australian vineyards.

Tetila, E.C., Brandoli Machado, B., Menezes, G.V., de Souza Belete, N.A., Astolfi, G., Pistori, H., 2020. A Deep-Learning Approach for Automatic Counting of Soybean Insect

Pests. IEEE Geosci. Remote Sens. Lett. 17, 1837–1841. https://doi.org/10.1109/LGRS.2019.2954735

Tharwat, A., Schenck, W., 2021. A conceptual and practical comparison of PSO-style optimization algorithms. Expert Syst. Appl. 167, 114430. https://doi.org/10.1016/j.eswa.2020.114430

The MathWorks Inc., 2022. The MathWorks Inc.

Tian, Y., Yang, G., Wang, Z., Wang, H., Li, E., Liang, Z., 2019. Apple detection during different growth stages in orchards using the improved YOLO-V3 model. Comput. Electron. Agric. 157, 417–426. https://doi.org/10.1016/j.compag.2019.01.012

Tindell, K.W., Burns, A., Wellings, A.J., 1992. Allocating hard real-time tasks: An NP-Hard problem made easy. Real-Time Syst. 4, 145–165. https://doi.org/10.1007/BF00365407

Tisseyre, B., Ojeda, H., Taylor, J., 2007. New technologies and methodologies for site-specific viticulture. J. Int. Sci. Vigne Vin 41, 63–76. https://doi.org/10.20870/oeno-one.2007.41.2.852

Tona, E., Calcante, A., Oberti, R., 2018. The profitability of precision spraying on specialty crops: a technical–economic analysis of protection equipment at increasing technological levels. Precis. Agric. 19, 606–629. https://doi.org/10.1007/s11119-017-9543-4

Torres, A. m., Palacios, S. a., Yerkovich, N., Palazzini, J. m., Battilani, P., Leslie, J. f., Logrieco, A. f., Chulze, S. n., 2019. Fusarium head blight and mycotoxins in wheat: prevention and control strategies across the food chain. World Mycotoxin J. 12, 333–355. https://doi.org/10.3920/WMJ2019.2438

Torres-Sánchez, J., Mesas-Carrascosa, F.J., Santesteban, L.-G., Jiménez-Brenes, F.M., Oneka, O., Villa-Llop, A., Loidi, M., López-Granados, F., 2021. Grape Cluster Detection Using UAV Photogrammetric Point Clouds as a Low-Cost Tool for Yield Forecasting in Vineyards. Sensors 21, 3083. https://doi.org/10.3390/s21093083

Torrey, L., Shavlik, J., 2010. Transfer Learning, in: Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques. IGI Global, pp. 242–264.

Toth, P., Vigo, D. (Eds.), 2002. The Vehicle Routing Problem. Society for Industrial and Applied Mathematics. https://doi.org/10.1137/1.9780898718515

Tractores y Máquinas, 2023. Calculadora de Precios de Tractores [WWW Document]. Tractores Máquinas. URL https://www.tractoresymaquinas.com/calculadora-precios-tractores/ (accessed 4.13.24).

Tsouros, D.C., Bibi, S., Sarigiannidis, P.G., 2019. A Review on UAV-Based Applications for Precision agriculture. Information 10, 349. https://doi.org/10.3390/info10110349

Tu, S., Pang, J., Liu, H., Zhuang, N., Chen, Y., Zheng, C., Wan, H., Xue, Y., 2020. Passion fruit detection and counting based on multiple scale faster R-CNN using RGB-D images. Precis. Agric. 21, 1072–1091. https://doi.org/10.1007/s11119-020-09709-3

Tu, S., Zeng, Q., Liang, Y., Liu, X., Huang, L., Weng, S., Huang, Q., 2022. Automated Behavior Recognition and Tracking of Group-Housed Pigs with an Improved DeepSORT Method. Agriculture 12, 1907. https://doi.org/10.3390/agriculture12111907

Tudi, M., Li, Hairong, Li, Hongying, Wang, L., Lyu, J., Yang, L., Tong, S., Yu, Q.J., Ruan, H.D., Atabila, A., Phung, D.T., Sadler, R., Connell, D., 2022. Exposure Routes and Health Risks Associated with Pesticide Application. Toxics 10, 335. https://doi.org/10.3390/toxics10060335

Tuyttens, F.A.M., Molento, C.F.M., Benaissa, S., 2022. Twelve Threats of Precision Livestock Farming (PLF) for Animal Welfare. Front. Vet. Sci. 9.

Tzanidakis, C., Simitzis, P., Arvanitis, K., Panagakis, P., 2021. An overview of the current trends in precision pig farming technologies. Livest. Sci. 249, 104530. https://doi.org/10.1016/j.livsci.2021.104530

United Nations, 2015a. Transforming our world: the 2030 Agenda for Sustainable Development [WWW Document]. URL https://sdgs.un.org/2030agenda (accessed 6.17.24).

United Nations, 2015b. Sustainable Development Goals [WWW Document]. U. N. Sustain. Dev. URL https://www.un.org/sustainabledevelopment/ (accessed 9.12.23).

United Nations Department of Economic and Social Affairs, 2022. UN DESA World Population Prospects | Knowledge for policy [WWW Document]. URL https://knowledge4policy.ec.europa.eu/dataset/ds00070_en (accessed 1.23.24).

United Nations Department of Economic and Social Affairs, Population Division, 2022. World Population Prospects 2022: Summary of Results (No. DESA/POP/2022/TR/NO. 3.). UN.

Valente, J., Ariza-Sentís, M., Vélez, S., 2023. Drone-ACO-ACPP [WWW Document]. GitHub Repos. URL https://github.com/saidlab-team/Drone-ACO-ACPP

Valente, J., Del Cerro, J., Barrientos, A., Sanz, D., 2013. Aerial coverage optimization in precision agriculture management: A musical harmony inspired approach. Comput. Electron. Agric. 99, 153–159. https://doi.org/10.1016/j.compag.2013.09.008

Valente, J., Hiremath, S., Ariza-Sentís, M., Doldersum, M., Kooistra, L., 2022. Mapping of Rumex obtusifolius in nature conservation areas using very high resolution UAV imagery and deep learning. Int. J. Appl. Earth Obs. Geoinformation 112, 102864. https://doi.org/10.1016/j.jag.2022.102864

van der Zande, Lisette.E., Guzhva, O., Rodenburg, T.B., 2021. Individual Detection and Tracking of Group Housed Pigs in Their Home Pen Using Computer Vision. Front. Anim. Sci. 2. https://doi.org/10.3389/fanim.2021.669312

Van Horn, G., Mac Aodha, O., Song, Y., Cui, Y., Sun, C., Shepard, A., Adam, H., Perona, P., Belongie, S., 2018. The iNaturalist Species Classification and Detection Dataset. https://doi.org/10.48550/arXiv.1707.06642

Vargas, R., Mosavi, A., Ruiz, R., 2017. Deep learning: A review (Working Paper).

Vasconez, J.P., Delpiano, J., Vougioukas, S., Auat Cheein, F., 2020. Comparison of convolutional neural networks in fruit detection and counting: A comprehensive evaluation. Comput. Electron. Agric. 173, 105348. https://doi.org/10.1016/j.compag.2020.105348

Vasuki, A., 2020. Nature-Inspired Optimization Algorithms. Chapman and Hall/CRC, New York. https://doi.org/10.1201/9780429289071

Vayssade, J.-A., Godard, X., Bonneau, M., 2023. Wizard: Unsupervised goats tracking algorithm. Comput. Electron. Agric. 209, 107831. https://doi.org/10.1016/j.compag.2023.107831

Vázquez Torres, E., 2010. Análisis de los costes de mecanización y alternativas para mejorar los rendimientos de una explotación de viña.

Velázquez-Martínez, O., Valio, J., Santasalo-Aarnio, A., Reuter, M., Serna-Guerrero, R., 2019. A Critical Review of Lithium-Ion Battery Recycling Processes from a Circular Economy Perspective. Batteries 5, 68. https://doi.org/10.3390/batteries5040068

Vélez, S., Ariza-Sentís, M., Valente, J., 2023a. Mapping the spatial variability of Botrytis bunch rot risk in vineyards using UAV multispectral imagery. Eur. J. Agron. 142, 126691. https://doi.org/10.1016/j.eja.2022.126691

Vélez, S., Ariza-Sentís, M., Valente, J., 2023b. Dataset on unmanned aerial vehicle multispectral images acquired over a vineyard affected by Botrytis cinerea in northern Spain. Data Brief 46, 108876. https://doi.org/10.1016/j.dib.2022.108876

Vélez, S., Ariza-Sentís, M., Valente, J., Bengochea-Guevara, J.M., Conejero, M.N., Montes, H., Ribeiro, Á., Cueva, M., Nistal, V., Prieto, D., González, M., Álvarez, S., Rodríguez, E., 2023c. Automatic detection of woody crop diseases combining aerial-ground robots and network sensors: An upscaling remote sensing approach, in: Abstract Book. Presented at the 14th European Conference on Precision agriculture, Bologna, Italy, pp. 189–190.

Vélez, S., Barajas, E., Rubio, J.A., Vacas, R., Poblete-Echeverría, C., 2020. Effect of Missing Vines on Total Leaf Area Determined by NDVI Calculated from Sentinel Satellite Data: Progressive Vine Removal Experiments. Appl. Sci. 10, 3612. https://doi.org/10.3390/app10103612

Vélez, S., Poblete-Echeverría, C., Rubio, J., Vacas, R., Barajas, E., 2021a. Estimation of Leaf Area Index in vineyards by analysing projected shadows using UAV imagery. OENO One 55, 159–180. https://doi.org/10.20870/oeno-one.2021.55.4.4639

Vélez, S., Rançon, F., Barajas, E., Brunel, G., Rubio, J.A., Tisseyre, B., 2022. Potential of functional analysis applied to Sentinel-2 time-series to assess relevant agronomic parameters at the within-field level in viticulture. Comput. Electron. Agric. 194, 106726. https://doi.org/10.1016/j.compag.2022.106726

Velusamy, P., Rajendran, S., Mahendran, R.K., Naseer, S., Shafiq, M., Choi, J.-G., 2022. Unmanned Aerial Vehicles (UAV) in Precision agriculture: Applications and Challenges. Energies 15, 217. https://doi.org/10.3390/en15010217

Verhaegen, I., Van Huylenbroeck, G., 2001. Costs and benefits for farmers participating in innovative marketing channels for quality food products. J. Rural Stud. 17, 443–456. https://doi.org/10.1016/S0743-0167(01)00017-1

Verma, S., Tripathi, S., Singh, A., Ojha, M., Saxena, R.R., 2021. Insect Detection and Identification using YOLO Algorithms on Soybean Crop, in: TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON). Presented at the TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON), pp. 272–277. https://doi.org/10.1109/TENCON54134.2021.9707354

Vermeulen, G.D., Tullberg, J.N., Chamen, W.C.T., 2010. Controlled Traffic Farming, in: Dedousis, A.P., Bartzanas, T. (Eds.), Soil Engineering. Springer, Berlin, Heidelberg, pp. 101–120. https://doi.org/10.1007/978-3-642-03681-1_8

Vijayakumar, V., Ampatzidis, Y., Schueller, J.K., Burks, T., 2023. Smart spraying technologies for precision weed management: A review. Smart Agric. Technol. 6, 100337. https://doi.org/10.1016/j.atech.2023.100337

Villacrés, J., Viscaino, M., Delpiano, J., Vougioukas, S., Auat Cheein, F., 2023. Apple orchard production estimation using deep learning strategies: A comparison of tracking-by-detection algorithms. Comput. Electron. Agric. 204, 107513. https://doi.org/10.1016/j.compag.2022.107513

Voigtlaender, P., Krause, M., Osep, A., Luiten, J., Sekar, B.B.G., Geiger, A., Leibe, B., 2019. MOTS: Multi-Object Tracking and Segmentation, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 7934–7943. https://doi.org/10.1109/CVPR.2019.00813

Vu, Q., Raković, M., Delic, V., Ronzhin, A., 2018. Trends in Development of UAV-UGV Cooperation Approaches in Precision agriculture, in: Ronzhin, A., Rigoll, G., Meshcheryakov, R. (Eds.), Interactive Collaborative Robotics. Springer International

Publishing, Cham, pp. 213–221. https://doi.org/10.1007/978-3-319-99582-3_22
Wachenheim, C., Fan, L., Zheng, S., 2021. Adoption of unmanned aerial vehicles for pesticide application: Role of social network, resource endowment, and perceptions. Technol. Soc. 64, 101470. https://doi.org/10.1016/j.techsoc.2020.101470
Wael, F., 2020. A Comprehensive Vehicle-Detection-and-Tracking Technique for Autonomous Driving. Int. J. Comput. Digit. Syst. 9, 567–580. https://doi.org/10.12785/ijcds/090405
Wakchaure, M., Patle, B.K., Mahindrakar, A.K., 2023. Application of AI techniques and robotics in agriculture: A review. Artif. Intell. Life Sci. 3, 100057. https://doi.org/10.1016/j.ailsci.2023.100057
Wan, S., Goudos, S., 2020. Faster R-CNN for multi-class fruit detection using a robotic vision system. Comput. Netw. 168, 107036. https://doi.org/10.1016/j.comnet.2019.107036
Wang, D., Cao, W., Zhang, F., Li, Z., Xu, S., Wu, X., 2022. A Review of Deep Learning in Multiscale Agricultural Sensing. Remote Sens. 14, 559. https://doi.org/10.3390/rs14030559
Wang, D., Song, H., Tie, Z., Zhang, W., He, D., 2016. Recognition and localization of occluded apples using K-means clustering algorithm and convex hull theory: a comparison. Multimed. Tools Appl. 75, 3177–3198. https://doi.org/10.1007/s11042-014-2429-9
Wang, H., Zhang, S., Zhao, S., Wang, Q., Li, D., Zhao, R., 2022. Real-time detection and tracking of fish abnormal behavior based on improved YOLOV5 and SiamRPN++. Comput. Electron. Agric. 192, 106512. https://doi.org/10.1016/j.compag.2021.106512
Wang, H., Zhang, X., 2022. Real-time vehicle detection and tracking using 3D LiDAR. Asian J. Control 24, 1459–1469. https://doi.org/10.1002/asjc.2519
Wang, H.-J., Fu, Y., Zhao, Z.-Q., Yue, Y.-J., 2019. An Improved Ant Colony Algorithm of Robot Path planning for Obstacle Avoidance. J. Robot. 2019, e6097591. https://doi.org/10.1155/2019/6097591
Wang, M., Tighe, J., Modolo, D., 2020. Combining Detection and Tracking for Human Pose Estimation in Videos, in: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Seattle, WA, USA, pp. 11085–11093. https://doi.org/10.1109/CVPR42600.2020.01110
Wang, R., Li, R., Chen, T., Zhang, J., Xie, C., Qiu, K., Chen, P., Du, J., Chen, H., Shao, F., Hu, H., Liu, H., 2022. An automatic system for pest recognition and forecasting. Pest Manag. Sci. 78, 711–721. https://doi.org/10.1002/ps.6684
Wang, R., Liu, L., Xie, C., Yang, P., Li, R., Zhou, M., 2021. AgriPest: A Large-Scale Domain-Specific Benchmark Dataset for Practical Agricultural Pest Detection in the Wild. Sensors 21, 1601. https://doi.org/10.3390/s21051601
Wang, S., Song, J., Qi, P., Yuan, C., Wu, H., Zhang, L., Liu, W., Liu, Y., He, X., 2022. Design and development of orchard autonomous navigation spray system. Front. Plant Sci. 13. https://doi.org/10.3389/fpls.2022.960686
Wang, Y., An, N., Wen, L., Wang, L., Jiang, X., Hou, F., Yin, Y., Liang, J., 2021. Recent progress on the recycling technology of Li-ion batteries. J. Energy Chem. 55, 391–419. https://doi.org/10.1016/j.jechem.2020.05.008
Wang, Y., Doherty, J.F., Van Dyck, R.E., 2000. Moving object tracking in video: 29th Applied Imagery Pattern Recognition Workshop, AIPR 2000. Proc. - 29th Appl.

Imag. Pattern Recognit. Workshop 2000-January, 95–101. https://doi.org/10.1109/AIPRW.2000.953609
Wang, Z., Walsh, K., Koirala, A., 2019. Mango Fruit Load Estimation Using a Video Based MangoYOLO—Kalman Filter—Hungarian Algorithm Method. Sensors 19, 2742. https://doi.org/10.3390/s19122742
Warman, C., Sullivan, C.M., Preece, J., Buchanan, M.E., Vejlupkova, Z., Jaiswal, P., Fowler, J.E., 2021. A cost-effective maize ear phenotyping platform enables rapid categorization and quantification of kernels. Plant J. 106, 566–579. https://doi.org/10.1111/tpj.15166
Welch, G., Bishop, G., 2006. An Introduction to the Kalman Filter. Proc Siggraph Course 8.
Wen, C., Chen, Hongrui, Ma, Z., Zhang, T., Yang, C., Su, H., Chen, Hongbing, 2022. Pest-YOLO: A model for large-scale multi-class dense and tiny pest detection and counting. Front. Plant Sci. 13.
Weng, X., Wang, J., Held, D., Kitani, K., 2020. 3D Multi-Object Tracking: A Baseline and New Evaluation Metrics, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Presented at the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 10359–10366. https://doi.org/10.1109/IROS45743.2020.9341164
White, B., 2012. Agriculture and the Generation Problem: Rural Youth, Employment and the Future of Farming. IDS Bull. 43, 9–19. https://doi.org/10.1111/j.1759-5436.2012.00375.x
Wojke, N., Bewley, A., Paulus, D., 2017. Simple online and realtime tracking with a deep association metric, in: 2017 IEEE International Conference on Image Processing (ICIP). Presented at the 2017 IEEE International Conference on Image Processing (ICIP), pp. 3645–3649. https://doi.org/10.1109/ICIP.2017.8296962
Wosner, O., Farjon, G., Bar-Hillel, A., 2021. Object detection in agricultural contexts: A multiple resolution benchmark and comparison to human. Comput. Electron. Agric. 189, 106404. https://doi.org/10.1016/j.compag.2021.106404
Wu, X., Zhan, C., Lai, Y.-K., Cheng, M.-M., Yang, J., 2019. IP102: A Large-Scale Benchmark Dataset for Insect Pest Recognition, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 8779–8788. https://doi.org/10.1109/CVPR.2019.00899
Wu, Y.N., 2011. Data Augmentation, Internal Representation, and Unsupervised Learning. J. Comput. Graph. Stat. 20, 581–583. https://doi.org/10.1198/jcgs.2011.203b
Wutke, M., Heinrich, F., Das, P.P., Lange, A., Gentz, M., Traulsen, I., Warns, F.K., Schmitt, A.O., Gültas, M., 2021. Detecting Animal Contacts—A Deep Learning-Based Pig Detection and Tracking Approach for the Quantification of Social Contacts. Sensors 21, 7512. https://doi.org/10.3390/s21227512
Xiang, L., Gai, J., Bao, Y., Yu, J., Schnable, P.S., Tang, L., 2023. Field-based robotic leaf angle detection and characterization of maize plants using stereo vision and deep convolutional neural networks. J. Field Robot. 40, 1034–1053. https://doi.org/10.1002/rob.22166
Xiao, C., Wang, B., Zhao, D., Wang, C., 2023. Comprehensive investigation on Lithium batteries for electric and hybrid-electric unmanned aerial vehicle applications. Therm. Sci. Eng. Prog. 38, 101677. https://doi.org/10.1016/j.tsep.2023.101677
Xiao, S., Ye, Y., Fei, S., Chen, H., Zhang, B., Li, Q., Cai, Z., Che, Y., Wang, Q., Ghafoor, A., Bi, K., Shao, K., Wang, R., Guo, Y., Li, B., Zhang, R., Chen, Z., Ma, Y., 2023. High-throughput calculation of organ-scale traits with reconstructed accurate 3D canopy structures using a UAV RGB camera with an advanced cross-circling oblique route.

ISPRS J. Photogramm. Remote Sens. 201, 104–122. https://doi.org/10.1016/j.isprsjprs.2023.05.016

Xin, F., Zhao, J., Zhou, Y., Wang, G., Han, X., Fu, W., Deng, J., Lan, Y., 2018. Effects of Dosage and Spraying Volume on Cotton Defoliants Efficacy: A Case Study Based on Application of Unmanned Aerial Vehicles. Agronomy 8, 85. https://doi.org/10.3390/agronomy8060085

Xiong, J., Liu, Z., Chen, S., Liu, B., Zheng, Z., Zhong, Z., Yang, Z., Peng, H., 2020. Visual detection of green mangoes by an unmanned aerial vehicle in orchards based on a deep learning method. Biosyst. Eng. 194, 261–272. https://doi.org/10.1016/j.biosystemseng.2020.04.006

Xiong, Y., Ge, Y., From, P.J., 2021. An improved obstacle separation method using deep learning for object detection and tracking in a hybrid visual control loop for fruit picking in clusters. Comput. Electron. Agric. 191, 106508. https://doi.org/10.1016/j.compag.2021.106508

Xu, B., Wang, W., Guo, L., Chen, G., Wang, Y., Zhang, W., Li, Y., 2021. Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle. Agriculture 11, 1062. https://doi.org/10.3390/agriculture11111062

Xu, G., Khan, A.S., Moshayedi, A.J., Zhang, X., Shuxin, Y., 2022. The Object detection, Perspective and Obstacles In Robotic: A Review : EAI Endorsed Trans. AI Robot. 1, e13–e13. https://doi.org/10.4108/airo.v1i1.2709

Xu, J., Gu, B., Tian, G., 2022. Review of agricultural IoT technology. Artif. Intell. Agric. 6, 10–22. https://doi.org/10.1016/j.aiia.2022.01.001

Xu, J., Mishra, P., 2022. Combining deep learning with chemometrics when it is really needed: A case of real time object detection and spectral model application for spectral image processing. Anal. Chim. Acta 1202, 339668. https://doi.org/10.1016/j.aca.2022.339668

Xu, X., Wang, L., Shu, M., Liang, X., Ghafoor, A.Z., Liu, Y., Ma, Y., Zhu, J., 2022. Detection and Counting of Maize Leaves Based on Two-Stage Deep Learning with UAV-Based RGB Image. Remote Sens. 14, 5388. https://doi.org/10.3390/rs14215388

Xu, Y., Chen, Q., Kong, S., Xing, L., Wang, Q., Cong, X., Zhou, Y., 2022. Real-time object detection method of melon leaf diseases under complex background in greenhouse. J. Real-Time Image Process. 19, 985–995. https://doi.org/10.1007/s11554-022-01239-7

Xu, Y., Han, Y., Sun, Z., Gu, W., Jin, Y., Xue, X., Lan, Y., 2023. Path planning Optimization With Multiple Pesticide and Power Loading Bases Using Several Unmanned Aerial Systems on Segmented Agricultural Fields. IEEE Trans. Syst. Man Cybern. Syst. 53, 1882–1894. https://doi.org/10.1109/TSMC.2022.3205695

Xu, Z., Zhang, W., Tan, X., Yang, W., Huang, H., Wen, S., Ding, E., Huang, L., 2020. Segment as Points for Efficient Online Multi-Object Tracking and Segmentation, in: Vedaldi, A., Bischof, H., Brox, T., Frahm, J.-M. (Eds.), Computer Vision – ECCV 2020, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 264–281. https://doi.org/10.1007/978-3-030-58452-8_16

Xue, X., Lan, Y., Sun, Z., Chang, C., Hoffmann, W.C., 2016. Develop an unmanned aerial vehicle based automatic aerial spraying system. Comput. Electron. Agric. 128, 58–66. https://doi.org/10.1016/j.compag.2016.07.022

Yang, F., Chang, X., Dang, C., Zheng, Z., Sakti, S., Nakamura, S., Wu, Y., 2021. ReMOTS: Self-Supervised Refining Multi-Object Tracking and Segmentation. https://doi.org/10.48550/arXiv.2007.03200

Yang, H., Chang, F., Huang, Y., Xu, M., Zhao, Y., Ma, L., Su, H., 2022. Multi-object tracking using Deep SORT and modified CenterNet in cotton seedling counting. Comput. Electron. Agric. 202, 107339. https://doi.org/10.1016/j.compag.2022.107339

Yang, J., Wang, X., Li, Z., Yang, P., Luo, X., Zhang, K., Zhang, S., Chen, L., 2016. Path planning of unmanned aerial vehicles for farmland information monitoring based on WSN, in: 2016 12th World Congress on Intelligent Control and Automation (WCICA). Presented at the 2016 12th World Congress on Intelligent Control and Automation (WCICA), pp. 2834–2838. https://doi.org/10.1109/WCICA.2016.7578794

Yang, L., Fan, Y., Xu, N., 2019. Video Instance Segmentation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). pp. 5188–5197.

Yang, S., Zheng, L., He, P., Wu, T., Sun, S., Wang, M., 2021. High-throughput soybean seeds phenotyping with convolutional neural networks and transfer learning. Plant Methods 17, 50. https://doi.org/10.1186/s13007-021-00749-y

Yao, L., Zhou, G., Ni, Z., Zhang, P., Zhu, S., 2015. Matching method for fruit surface image based on scale invariant feature transform algorithm. Trans. Chin. Soc. Agric. Eng. 31, 161–166.

Yao, P., Wang, H., Su, Z., 2016. Cooperative path planning with applications to target tracking and obstacle avoidance for multi-UAVs. Aerosp. Sci. Technol. 54, 10–22. https://doi.org/10.1016/j.ast.2016.04.002

Yilmaz, A., Javed, O., Shah, M., 2006. Object tracking: A survey. ACM Comput. Surv. 38, 13-es. https://doi.org/10.1145/1177352.1177355

Yousefi, D.B.M., Rafie, A.S.M., Al-Haddad, S.A.R., Azrad, S., 2022. A Systematic Literature Review on the Use of Deep Learning in Precision Livestock Detection and Localization Using Unmanned Aerial Vehicles. IEEE Access 10, 80071–80091. https://doi.org/10.1109/ACCESS.2022.3194507

Yowtak, K., Imiola, J., Andrews, M., Cardillo, K., Skerlos, S., 2020. Comparative life cycle assessment of unmanned aerial vehicles, internal combustion engine vehicles and battery electric vehicles for grocery delivery. Procedia CIRP, 27th CIRP Life Cycle Engineering Conference (LCE2020) Advancing Life Cycle Engineering : from technological eco-efficiency to technology that supports a world that meets the development goals and the absolute sustainability 90, 244–250. https://doi.org/10.1016/j.procir.2020.02.003

Yu, K.-M., Lee, M.-G., Chi, S.-S., 2017. Dynamic path planning based on adaptable Ant colony optimization algorithm, in: 2017 Sixth International Conference on Future Generation Communication Technologies (FGCT). Presented at the 2017 Sixth International Conference on Future Generation Communication Technologies (FGCT), pp. 1–7. https://doi.org/10.1109/FGCT.2017.8103732

Yun, C., Kim, H.-J., Jeon, C.-W., Gang, M., Lee, W.S., Han, J.G., 2021. Stereovision-based ridge-furrow detection and tracking for auto-guided cultivator. Comput. Electron. Agric. 191, 106490. https://doi.org/10.1016/j.compag.2021.106490

Zabawa, L., Kicherer, A., Klingbeil, L., Milioto, A., Töpfer, R., Kuhlmann, H., Roscher, R., 2019. Detection of Single Grapevine Berries in Images Using Fully Convolutional Neural Networks, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). Presented at the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 2571–2579. https://doi.org/10.1109/CVPRW.2019.00313

Zabawa, L., Kicherer, A., Klingbeil, L., Töpfer, R., Kuhlmann, H., Roscher, R., 2020. Counting of Grapevine Berries in Images via Semantic Segmentation using Convolutional Neural Networks. ISPRS J. Photogramm. Remote Sens. 164, 73–83. https://doi.org/10.1016/j.isprsjprs.2020.04.002

Zhai, Z., Martínez, J.F., Beltran, V., Martínez, N.L., 2020. Decision support systems for agriculture 4.0: Survey and challenges. Comput. Electron. Agric. 170, 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhang, C., Ding, H., Shi, Q., Wang, Y., 2022. Grape Cluster Real-Time Detection in Complex Natural Scenes Based on YOLOv5s Deep Learning Network. Agriculture 12, 1242. https://doi.org/10.3390/agriculture12081242

Zhang, C., Si, Y., Lamkey, J., Boydston, R.A., Garland-Campbell, K.A., Sankaran, S., 2018. High-Throughput Phenotyping of Seed/Seedling Evaluation Using Digital Image Analysis. Agronomy 8, 63. https://doi.org/10.3390/agronomy8050063

Zhang, C., Valente, J., Kooistra, L., Guo, L., Wang, W., 2021. Orchard management with small unmanned aerial vehicles: a survey of sensing and analysis approaches. Precis. Agric. 22, 2007–2052. https://doi.org/10.1007/s11119-021-09813-y

Zhang, C., Zhen, Z., Wang, D., Li, M., 2010. UAV path planning method based on ant colony optimization, in: 2010 Chinese Control and Decision Conference. Presented at the 2010 Chinese Control and Decision Conference, pp. 3790–3792. https://doi.org/10.1109/CCDC.2010.5498477

Zhang, K., Wu, Q., Chen, Y., 2021. Detecting soybean leaf disease from synthetic image using multi-feature fusion faster R-CNN. Comput. Electron. Agric. 183, 106064. https://doi.org/10.1016/j.compag.2021.106064

Zhang, Lefei, Zhang, Liangpei, 2022. Artificial Intelligence for Remote Sensing Data Analysis: A review of challenges and opportunities. IEEE Geosci. Remote Sens. Mag. 10, 270–294. https://doi.org/10.1109/MGRS.2022.3145854

Zhang, R., Zheng, Y., Yao, Z., Vanaphuti, P., Ma, X., Bong, S., Chen, M., Liu, Y., Cheng, F., Yang, Z., Wang, Y., 2020. Systematic Study of Al Impurity for NCM622 Cathode Materials. ACS Sustain. Chem. Eng. 8, 9875–9884. https://doi.org/10.1021/acssuschemeng.0c02965

Zhang, Wei, Huang, H., Sun, Y., Wu, X., 2022. AgriPest-YOLO: A rapid light-trap agricultural pest detection method based on deep learning. Front. Plant Sci. 13, 1079384. https://doi.org/10.3389/fpls.2022.1079384

Zhang, W., Ning, Y., Suo, C., 2019. A Method Based on Multi-Sensor Data Fusion for UAV Safety Distance Diagnosis. Electronics 8, 1467. https://doi.org/10.3390/electronics8121467

Zhang, Wenli, Wang, J., Liu, Y., Chen, K., Li, H., Duan, Y., Wu, W., Shi, Y., Guo, W., 2022a. Deep-learning-based in-field citrus fruit detection and tracking. Hortic. Res. 9, uhac003. https://doi.org/10.1093/hr/uhac003

Zhang, Wenli, Wang, J., Liu, Y., Chen, K., Li, H., Duan, Y., Wu, W., Shi, Y., Guo, W., 2022b. Deep-learning-based in-field citrus fruit detection and tracking. Hortic. Res. 9, uhac003. https://doi.org/10.1093/hr/uhac003

Zhang, Wenli, Wang, J., Liu, Y., Chen, K., Li, H., Duan, Y., Wu, W., Shi, Y., Guo, W., 2022c. Deep-learning-based in-field citrus fruit detection and tracking. Hortic. Res. 9, uhac003. https://doi.org/10.1093/hr/uhac003

Zhang, X., Lu, H., Hao, C., Li, J., Cheng, B., Li, Y., Rupnow, K., Xiong, J., Huang, T., Shi, H., Hwu, W., Chen, D., 2020. SkyNet: a Hardware-Efficient Method for Object detection and tracking on Embedded Systems. https://doi.org/10.48550/arXiv.1909.09709

Zhang, Y., Song, C., Zhang, D., 2020. Deep Learning-Based Object detection Improvement for Tomato Disease. IEEE Access 8, 56607–56614. https://doi.org/10.1109/ACCESS.2020.2982456

Zhang, Y., Sun, P., Jiang, Y., Yu, D., Weng, F., Yuan, Z., Luo, P., Liu, W., Wang, X., 2022. ByteTrack: Multi-object Tracking by Associating Every Detection Box, in: Avidan, S., Brostow, G., Cissé, M., Farinella, G.M., Hassner, T. (Eds.), Computer Vision – ECCV 2022, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 1–21. https://doi.org/10.1007/978-3-031-20047-2_1

Zhang, Z., Kayacan, E., Thompson, B., Chowdhary, G., 2020. High precision control and deep learning-based corn stand counting algorithms for agricultural robot. Auton. Robots 44, 1289–1302. https://doi.org/10.1007/s10514-020-09915-y

Zhao, R., Zhu, Y., Li, Y., 2022. An end-to-end lightweight model for grape and picking point simultaneous detection. Biosyst. Eng. 223, 174–188. https://doi.org/10.1016/j.biosystemseng.2022.08.013

Zhao, W., Yamada, W., Li, T., Digman, M., Runge, T., 2020. Augmenting Crop Detection for Precision agriculture with Deep Visual Transfer Learning—A Case Study of Bale Detection. Remote Sens. 13, 23. https://doi.org/10.3390/rs13010023

Zheng, Caiwang, Abd-Elrahman, A., Whitaker, V., 2021. Remote Sensing and Machine Learning in Crop Phenotyping and Management, with an Emphasis on Applications in Strawberry Farming. Remote Sens. 13, 531. https://doi.org/10.3390/rs13030531

Zheng, Chan, Chen, P., Pang, J., Yang, X., Chen, C., Tu, S., Xue, Y., 2021. A mango picking vision algorithm on instance segmentation and key point detection from RGB images in an open orchard. Biosyst. Eng. 206, 32–54. https://doi.org/10.1016/j.biosystemseng.2021.03.012

Zheng, S., Ge, M., Li, C., Wang, C., Xue, A., 2010. New transition probablity for Ant Colony Optimization: global random-proportional rule, in: 2010 8th World Congress on Intelligent Control and Automation. Presented at the 2010 8th World Congress on Intelligent Control and Automation, pp. 2698–2702. https://doi.org/10.1109/WCICA.2010.5555079

Zheng, S., Zhou, C., Jiang, X., Huang, J., Xu, D., 2022. Progress on Infrared Imaging Technology in Animal Production: A Review. Sensors 22, 705. https://doi.org/10.3390/s22030705

Zheng, Y., Huang, D., Liu, S., Wang, Y., 2020. Cross-domain Object detection through Coarse-to-Fine Feature Adaptation. Presented at the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 13766–13775.

Zheng, Y.-Y., Kong, J.-L., Jin, X.-B., Wang, X.-Y., Su, T.-L., Zuo, M., 2019. CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision agriculture. Sensors 19, 1058. https://doi.org/10.3390/s19051058

Zheng, Z., Li, J., Qin, L., 2023a. YOLO-BYTE: An efficient multi-object tracking algorithm for automatic monitoring of dairy cows. Comput. Electron. Agric. 209, 107857. https://doi.org/10.1016/j.compag.2023.107857

Zheng, Z., Zhang, X., Qin, L., Yue, S., Zeng, P., 2023b. Cows' legs tracking and lameness detection in dairy cattle using video analysis and Siamese neural networks. Comput. Electron. Agric. 205, 107618. https://doi.org/10.1016/j.compag.2023.107618

Zhou, G., Zhang, W., Chen, A., He, M., Ma, X., 2019. Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion. IEEE Access 7, 143190–143206. https://doi.org/10.1109/ACCESS.2019.2943454

Zhou, L., Xiao, Q., Taha, M.F., Xu, C., Zhang, C., 2023. Phenotypic Analysis of Diseased Plant Leaves Using Supervised and Weakly Supervised Deep Learning. Plant Phenomics 5, 0022. https://doi.org/10.34133/plantphenomics.0022

Zhou, Y., Rui, T., Li, Y., Zuo, X., 2019. A UAV patrol system using panoramic stitching and object detection. Comput. Electr. Eng. 80, 106473. https://doi.org/10.1016/j.compeleceng.2019.106473

Zhu, F., He, M., Zheng, Z., 2020. Data augmentation using improved cDCGAN for plant vigor rating. Comput. Electron. Agric. 175, 105603. https://doi.org/10.1016/j.compag.2020.105603

Zhu, X., Vondrick, C., Ramanan, D., Fowlkes, C., 2012. Do We Need More Training Data or Better Models for Object detection?, in: Procedings of the British Machine Vision Conference 2012. Presented at the British Machine Vision Conference 2012, British Machine Vision Association, Surrey, p. 80.1-80.11. https://doi.org/10.5244/C.26.80

Zhuang, X., Zhang, T., 2019. Detection of sick broilers by digital image processing and deep learning. Biosyst. Eng. 179, 106–116. https://doi.org/10.1016/j.biosystemseng.2019.01.003

Zou, H., Lu, H., Li, Y., Liu, L., Cao, Z., 2020. Maize tassels detection: a benchmark of the state of the art. Plant Methods 16, 108. https://doi.org/10.1186/s13007-020-00651-z

Summary

Efficient and precise management is required for crops with added value, as is the case of crops trained in vertical trellis systems, such as fruit orchards and vineyards. This precision is essential to optimise inputs applied to the field, increase farmers' revenue, and boost the sustainability of the final product and the environmental impact of agricultural production. Farmers have recently been empowered with new technologies to tailor farming practices to specific conditions, improving traditional image processing techniques and reducing manual tasks. These technologies include Remote Sensing, Unmanned Aerial Vehicles (UAVs), and Artificial Intelligence, among others. They offer pivotal applications within precision farming (PF), also known as precision agriculture, to enhance crop monitoring and management practices, such as disease assessment, precise spraying, phenotyping, and yield estimation. Nevertheless, research focuses on detection and tracking algorithms but not how data is acquired. Proper data collection methods can already increase detection and tracking metrics if captured with the specific purpose for which data is gathered. Plants constantly change, so data collection should monitor these changes and assess the field environment's current status. Most research is conducted in experimental vineyards, which do not always represent the conditions of commercial vineyards. For example, leaf removal is performed in experimental vineyards to avoid fruit occlusion, but this practice is not common in commercial vineyards. The main objective of this study is to establish a framework to enhance data collection for improving agricultural operations such as disease assessment for precision spraying and phenotyping for yield forecasting, considering the field environment and avoiding fruit occlusion.

Chapter 2 provides a literature review of advancements in object detection and tracking within PF. The review highlights significant developments in detection and tracking techniques, focusing on their roles in enhancing crop and livestock management. Despite progress, challenges such as limited computational power, data overload, and the importance of model interpretability are emphasised. The need for open-source datasets and optimised data acquisition methods are identified as crucial steps forward.

Chapter 3 evaluates the use of UAVs, Unmanned Ground Vehicles (UGVs), and tractors for PF, particularly in Spraying. The study uses a two-phase framework: first, a survey flight gathers UAV multispectral imagery to generate Botrytis Bunch Rot risk maps for targeted

spraying routes. UAVs capture crop health data, allowing accurate disease hotspot detection. Second, the actual phytosanitary application flight is conducted. The procedure is automatised, and the script is open-source to enhance reproducibility. Results show UAVs are more effective in localised infection scenarios due to their ability to fly over plants and change rows in the vineyard. In low-density infection areas, UAVs travel 41% less distance and require 32% less spraying time compared to ground robots. However, in high-density scenarios, UAVs require significantly more time and distance due to frequent battery recharges.

In Chapter 4, object detection and tracking in PF: Phenotyping, is explored to test the UAV's ability to detect and assess clusters by flying close to plants. The study applies the PointTrack algorithm for bunch detection and tracking, and YOLACT and Spatial Embeddings for berry detection. It includes UAV RGB videos and their annotations as an open-source dataset. Results showed robust grape bunch detection, but berry tracking and counting faced challenges due to fruit occlusions and complex illumination conditions. The best MODSA metric for grape bunch detection is 66%, while tracking metrics are less favourable, with a strong correlation (R^2 = 0.62) and low RMSE of 32.5 (International Organisation of Vine and Wine (OIV) codes 202, 203, and 208). Spatial Embeddings achieves 79.5% accuracy in berry counting compared to YOLACT's 44.6%.

Chapter 5 presents an innovative path planning framework designed to improve data collection efficiency in crops trained in vertical trellis. It employs the two-phase framework developed in Chapter 3. The second flight uses the risk map models to optimise the UAV's path using the Ant Colony Optimisation Max-Min Ant System (ACO-MMAS) algorithm. This approach ensures comprehensive coverage by capturing images from multiple angles to mitigate occlusion issues, which hampers grape bunch detection. The optimised path planning reduced the length of UAV routes by up to 24% compared to traditional methods. This efficiency in path length translates to better resource allocation and reduced battery consumption, critical for UAV operations in agricultural fields, as identified in Chapter 3.

In Chapter 6, the multi-angle path planning is implemented in a commercial vineyard. PointTrack is used to extract and compare grape bunch detection and tracking metrics between single-angle and multiple-angle datasets. Experimental results show significant improvement in grape bunch detection, achieving up to 74% in fruit counting accuracy with multiple perspectives compared to up to 23% with the single-angle approach. Moreover, multiple-angle data achieves a higher correlation and lower RMSE for bunch phenotypic traits (OIV codes 202 and 203) compared to ground truth measurements ($R^2 = 0.53$, RMSE = 19.13), as bunches are observed in their full size. These findings underscore the importance of data acquisition strategies in improving performance for fruit detection, counting, and phenotyping.

The critical role of data collection methods in enhancing object detection and tracking metrics in PF scenarios is highlighted in this work. The two-phase framework combines mapping of the biophysical environment and detailed monitoring of grape bunches through a multiple-angle path planning approach to avoid fruit occlusion. Significant progress has been made in integrating object detection and tracking with PF. Implementing a multiple-view approach has shown notable improvements in data acquisition, leading to better detection performance. Future research should focus on refining data acquisition methods, providing more open-source datasets to boost automation, and enhancing algorithm robustness under varying conditions. These advancements will further strengthen the precision and sustainability of high-value crop management, ultimately benefiting farmers, society, and the environment.

Resum

En agricultura és necessària una gestió eficient i precisa per als cultius amb valor afegit, com és el cas dels cultius en espatllera, com ara fruiters i vinyes. Aquesta precisió és essencial per optimitzar els inputs aplicats al camp, augmentar els ingressos dels agricultors i millorar la sostenibilitat del producte final, així com reduir l'impacte ambiental. En els darrers anys, els agricultors han estat dotats de noves tecnologies per adaptar les pràctiques agrícoles a condicions específiques, millorant les tècniques tradicionals de processament d'imatges i reduint les tasques manuals. Aquestes tecnologies inclouen la teledetecció, els drons i la intel·ligència artificial, entre altres. Ofereixen aplicacions clau dins de l'agricultura de precisió per millorar el monitoratge i la gestió dels cultius, com l'avaluació de malalties, l’aplicació precisa de fitosanitaris, el fenotipat i la predicció del rendiment. No obstant això, la recerca es centra en els algoritmes de detecció i seguiment, però no en com es recullen les dades. Els mètodes adequats de recopilació de dades per si mateixos poden augmentar la qualitat de detecció si es capturen tenint en compte el propòsit específic pel qual es recullen. Les plantes canvien constantment, per la qual cosa la recopilació de dades hauria de monitoritzar aquests canvis i avaluar l'estat actual del camp. La major part de la recerca es realitza en vinyes experimentals, que no sempre representen les condicions de les vinyes comercials. Per exemple, en vinyes experimentals es practica la desfoliació per evitar que el fruit quedi amagat darrere de la fulla, però aquesta pràctica no és habitual en vinyes comercials. L'objectiu principal d'aquest estudi és establir un marc per millorar la recopilació de dades destinades a optimitzar les operacions agrícoles, com l'avaluació de malalties per a l’aplicació precisa de fitosanitaris o el fenotipat per a la predicció de rendiments, tenint en compte l’estat actual del camp i evitant que el fruit quedi ocult.

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List of publications

Peer-reviewed journal publications

From this thesis:

1. Ariza-Sentís, M., Baja, H., Vélez, S., Valente, J., 2023. Object detection and tracking on UAV RGB videos for early extraction of grape phenotypic traits. Comput. Electron. Agric. 211, 108051. https://doi.org/10.1016/j.compag.2023.108051
2. Ariza-Sentís, M., Vélez, S., Baja, H., Valenti, R.G., Valente, J., 2024. An aerial framework for Multi-View grape bunch detection and route Optimization using ACO. Comput. Electron. Agric. 221, 108972. https://doi.org/10.1016/j.compag.2024.108972
3. Ariza-Sentís, M., Vélez, S., Martínez-Peña, R., Baja, H., Valente, J., 2024. Object detection and tracking in Precision farming: a systematic review. Comput. Electron. Agric. 219, 108757. https://doi.org/10.1016/j.compag.2024.108757
4. Ariza-Sentís, M., Vélez, S., Valente, J., 2023. Dataset on UAV RGB videos acquired over a vineyard including bunch labels for object detection and tracking. Data Brief 46, 108848. https://doi.org/10.1016/j.dib.2022.108848
5. Ariza-Sentís, M., Vélez, S., Valente, J., 2023. BBR: An open-source standard workflow based on biophysical crop parameters for automatic Botrytis cinerea assessment in vineyards. SoftwareX 24, 101542. https://doi.org/10.1016/j.softx.2023.101542
6. Ariza-Sentís, M., Wang, K., Cao, Z., Vélez, S., Valente, J., 2024. GrapeMOTS: UAV vineyard dataset with MOTS grape bunch annotations recorded from multiple perspectives for enhanced object detection and tracking. Data Brief 54, 110432. https://doi.org/10.1016/j.dib.2024.110432
7. Vélez, S., Ariza-Sentís, M., Valente, J., 2023. Dataset on unmanned aerial vehicle multispectral images acquired over a vineyard affected by Botrytis cinerea in northern Spain. Data Brief 46, 108876. https://doi.org/10.1016/j.dib.2022.108876
8. Vélez, S., Ariza-Sentís, M., Valente, J., 2023. Mapping the spatial variability of Botrytis bunch rot risk in vineyards using UAV multispectral imagery. Eur. J. Agron. 142, 126691. https://doi.org/10.1016/j.eja.2022.126691

Contributions outside of this thesis:

1. Ariza-Sentís, M., Valente, J., Kooistra, L., Kramer, H., Mücher, S., 2023. Estimation of spinach (Spinacia oleracea) seed yield with 2D UAV data and deep learning. Smart Agric. Technol. 3, 100129. https://doi.org/10.1016/j.atech.2022.100129
2. Buunk, T., Vélez, S., Ariza-Sentís, M., Valente, J., 2023. Comparing Nadir and Oblique Thermal Imagery in UAV-Based 3D Crop Water Stress Index Applications for Precision viticulture with LiDAR Validation. Sensors 23, 8625. https://doi.org/10.3390/s23208625
3. Valente, J., Hiremath, S., Ariza-Sentís, M., Doldersum, M., Kooistra, L., 2022. Mapping of Rumex obtusifolius in nature conservation areas using very high resolution UAV imagery and deep learning. Int. J. Appl. Earth Obs. Geoinformation 112, 102864. https://doi.org/10.1016/j.jag.2022.102864
4. Vélez, S., Ariza-Sentís, M., Panić, M., Ivošević, B., Stefanović, D., Kaivosoja, J., Valente, J., 2024. Speeding up UAV-based crop variability assessment through a data fusion approach using spatial interpolation for site-specific management. Smart Agric. Technol. 8, 100488. https://doi.org/10.1016/j.atech.2024.100488
5. Vélez, S., Mier, G., Ariza-Sentís, M., Valente, J., 2024. Integrated Framework for Multipurpose UAV Path Planning in Hedgerow Systems considering the Biophysical Environment. Crop Protection. https://doi.org/10.1016/j.cropro.2024.106992
6. Vélez, S., Ariza-Sentís, M., Valente, J., 2024. EscaYard: Precision viticulture multimodal dataset of vineyards affected by Esca disease consisting of geotagged smartphone images, phytosanitary status, UAV 3D point clouds and Orthomosaics. Data Brief 54, 110497. https://doi.org/10.1016/j.dib.2024.110497
7. Vélez, S., Ariza-Sentís, M., Valente, J., 2023. VineLiDAR: High-resolution UAV-LiDAR vineyard dataset acquired over two years in northern Spain. Data Brief 51, 109686. https://doi.org/10.1016/j.dib.2023.109686

Publications under review

From this thesis:

1. Ariza-Sentís, M., Mier, G, Vélez, S., Valente, J., 2024. Comparative Analysis of UAVs, UGVs and Tractors for Precision Spraying in Vineyards: Addressing Economic, Energy, and Sustainability Aspects. Computers and Electronics in Agriculture [under review]
2. Ariza-Sentís, M., Baja, H, Vélez, S., van Essen, R., Valente, J., 2024. Comparative Analysis of Single-View and Multiple-View Data Collection Strategies for Detecting Partially-Occluded Grape Bunches: Field Trials. Journal of Agriculture and Food Research [under review]

Contributions outside of this thesis:

1. Vélez, S., Ariza-Sentís, M., Baja, H., Triviño, M., Cob-Parro, A.C., Mila, M., Valente., J., Web-based AI Framework Trained with UAV Videos for Smartphone-based Grape Detection and Vineyard Management. Heliyon [under review]
2. Spyrou, O., Ariza-Sentís, M., Vélez, S., Enhancing Education in Agriculture via XR-Based Digital Twins: A Novel Approach for the Next Generation. Computers & Education: X Reality [under review]
3. Vélez, S., Martínez-Peña, R., Valente, J., Ariza-Sentís, M., Pardo, M.A., A Novel Decision Support System for Generating Irrigation Ecolabels Based on the Resource Overutilization Ratio. Agricultural Water Management [under review]

Lastly, a total of 12 conference publications have been presented at several congresses, including the International Plant Phenotyping Symposium (2022), the 5th Iberian Robotics Conference (2022), FinDrones (2023), the 14th European Conference on Precision Agriculture (2023), the 5th International Electronic Conference on Remote Sensing session Remote sensing systems and techniques (2023), and the Agricultural Engineering challenges in existing and new agroecosystems (2024). Moreover, 6 manuscripts have been published in technical journals.

About the author

Mar Ariza Sentís was born on November 10, 1997, in Lleida, Spain. Growing up in a farming family, she developed a deep-rooted passion for agriculture early on. This interest led her to enrol in a degree program in Agricultural and Food Engineering at the University of Lleida. During her studies, she had the enriching experience of spending a year at Wageningen University, where she was exposed to new ideas and methodologies that significantly influenced her academic and professional path.

Inspired by her time in the Netherlands, Mar decided to further her education there. She subsequently enrolled in an MSc program in Geo-Information Science at Wageningen University. This program provided her with advanced knowledge and expertise to integrate technology with agriculture, preparing her well for her future endeavours.
After completing her master's degree, Mar embarked on a PhD journey, focusing on the use of Computer Vision and UAVs in precision viticulture. Her research is pioneering in its aim to combine advanced technology with traditional farming practices to improve efficiency and precision in viticulture.

Today, Mar works as an Agricultural Engineer, managing her own fields and applying precision agriculture methodologies to enhance the yield and sustainability of her family's 1,300-hectare farm. She oversees the cultivation of barley, wheat, almonds, and olive trees, continuously striving to improve agricultural practices and sustainability. In addition, she also serves as a project manager at a consultancy company, where she applies her expertise to guide projects aimed at optimising agricultural operations and sustainability.

Mar's journey reflects her dedication to agriculture and her innovative approach to integrating modern technology with traditional farming, leading the way towards a more sustainable future in agriculture.

Maria del Mar Ariza Sentís

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Wageningen School of Social Sciences

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2023	1
'Automatic Tracking of Grape clusters and early phenotyping from UAV video sequences'	IPPS 2022, Wageningen	2022	1
'Towards Automated UAV Image Processing Workflows in Precision viticulture: Challenges and Benefits'	ROBOT 2022, Zaragoza (Spain)	2022	1
'How drones are changing the way farm work is done'	EXPO 2023, Podgorica (Montenegro)	2023	1
'Grape counting in RGB videos – comparing two instance segmentation models'	ECPA 2023, Bologna (Italy)	2023	1
'Improving up-close Remote Sensing occluded areas in Vine-2 yards through customized multiple UAV Path planning'	ECRS 2023, online	2023	1
Peer reviewer	ISPRS Open Journal of Photogrammetry and Remote Sensing	2023	1
Peer reviewer	Big Earth Data	2023	1
A2 Integrating research in the corresponding discipline			
EU Drone License A1/A3	European Union Aviation Safety Agency	2022	3
EU Drone License A2	European Union Aviation Safety Agency	2022	3
Introduction to SQL	edX	2023	3
Drones for Agriculture: Prepare and Design Your Drone (UAV) Mission	WageningenX on edX	2023	3

B) General research related competences			
B1 Placing research in a broader scientific context			
Philosophy of social science	WASS	2023	3
Drainage in Agriculture: controlling water and salt levels in the soil	WageningenX on edX	2023	4
B2 Placing research in a societal context			
"*Utilització de drons i robots terrestres per detectar malalties i males herbes en el cultiu*"	Extensius	2022	1
"*Detección y seguimiento de racimos para fenotipado en vídeos laterales de dron*"	Agricultura	2023	1
"*Utilización de imágenes aéreas de dron para evaluar el riesgo de enfermedades fúngicas en viñedo*"	Agricultura	2023	1
"*Agricultura 5.0: Nueva era en la detección de enfermedades combinando robots aéreos, terrestres y sensores*"	Tierras	2023	1
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Teaching INF-33806 Big Data	INF	2022, 2023	2
Supervision of BSc, MSc students	INF	2022, 2023	2
Total			**35**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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