AGROS Disease Control Seed Potatoes

Report 2020-2023

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Disease detection in seed potatoes is time consuming and physically challenging. The availability of qualified disease selection specialist is becoming more and more a problem. This report is part of the Private Public Partnership Project AGROS and shows the results of detecting virus and Erwinia infections in seed potatoes based on vision technology and Artificial Intelligence. During 4 years data was collected in mainly experimental fields with a fairly high level of sick plants. The classification of plants in sick and healthy was done by neural network EfficientnetB_0. The data analysis showed that a high level of precision (between 80-90%) is possible. Generalization of the model was tested on other fields and different varieties.

Keywords: Disease control, seed potatoes, Erwinia, virus detection, vision technology

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Photo cover: WUR Field Crops (camera setup)

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Preface

The agricultural sector faces major challenges. Climate change leading to greater weather extremes, decline in biodiversity, soil compaction, energy transition, reduced use of plant protection products, etc., require a different way of looking at the agricultural system. Over the last decade, it became clear that precision agriculture is one of the tools to reach solutions. This led to the project SMARAGD (Smart Mechanization - Automation - Robotics for an Arable agriculture with Growth and Sustainability - 2017-2020) that focused on improving soil quality and taking advantage of opportunities potentially offered by mixed and strip cropping. The AGROS project can be seen as the follow-up project, building on the results and insights of the SMARAGD project.

The AGROS program is a collaboration between Wageningen University & Research (WUR) and 26 private partners, with funding from two of the Top Sector programs: Agri & Food and Horticulture & Starting Materials. AGROS stands for "Evolution to sustainable AGRicultural Operation Systems". The main goal is to develop tools that can support production based on natural biological and ecological processes, steering production toward sustainable use of inputs such as energy, water, crop protection products and labour. The knowledge from the research and experiments and professional guidance will benefit participating arable farmers, dairy farmers, greenhouse growers and technology companies.

The focus of the project in arable crops is the optimal use of the power of nature in food production. Ecology can be improved by choosing for mixed cropping: narrow strips of different crops where natural enemies find a good biotope in close range. Fixed traffic lanes in the field create beds without soil compaction and improved moisture availability. Implementation of new precision agriculture techniques can support this transition by reducing inputs and optimizing sustainability, increasing yields and therefor economic results. T

The project is composed of the following work packages:

- Development of transition paths: how will agriculture look like in 2040? Which scenarios are conceivable? And which first steps need to be taken?
- Integration of sensors, decision support and robotization in various domains: a)recognition and control of diseases and pests. b)disease detection in seed potatoes. c)weed control using vision and deep learning. d)sensor development for issues in open cultivation.
- Future infrastructure for data management and energy supply.

This report focuses on the topic of disease control in seed potatoes using vision technology and deep learning.

Summary

The Netherlands are the world's biggest producer of certified seed potatoes. In temperate climate regions, the main diseases of the seed potato crop are caused by viruses and bacterial infections (Dickeya and P. atrosepticum and P. c. subsp. Brasiliense). Farmers face the risk of declassification or rejection of this high value crop and spend a lot of effort to detect diseased plants and remove them before inspection by the Dutch General Inspection Service (NAK).

In this project the potential of a vision based AI application that can detect these diseases in seed potatoes is explored. The objective was to develop a robust algorithm for both diseases, that can work under different conditions (weather, soil) and in different varieties. After that, testing of such an application under practical conditions was part of the project and combined with an interaction with seed potato farmers, as well as participants of the seed potato value chain, to investigate the needs and expectations.

The major part of the project was related to the creation of an annotated data set, based on 4 years of data and different weather and soil conditions. Most of the data was collected on experimental fields with highly infected varieties. In the last year also collected data on other locations besides Lelystad (Tollebeek, Valthermond). The data analyses was done with the EfficientnetB_0 neural network. A model trained on data of 2020-2023 resulted in an accuracy of about 80%. Testing the model with different subsets, based on location or on different varieties show a similar level of precision. The best test use case was the one done at the NAK location in Tollebeek on a field with 200 different varieties in small plots. The precision level of the global model dropped to a level of 74%. This result shows that a further improvement of the algorithm by extension of the dataset is needed to improve the generalization of the model.

A challenge for a vision based system is to detect symptoms of Erwinia that are sometimes located deeper in the crop foliage. That is why a technical setup was chosen with 3 cameras: one top view and 2 cameras under an angle of about 30 degrees. A first comparison between the model's performance when using only the top view camera or using a combination of the top view camera and 2 cameras looking at the plant under a 30degree angle, show similar results when based on majority voting system. Additional research is needed to test different decision making approaches.

The developments in the project were shared with farmers and representatives of seed potato value chain. Farmers were positive about the quality level of the algorithm presented. They are aware that creating a robust vision - AI base system will need extra efforts. Also meeting the quality level used by the Dutch General Inspection Service (NAK) needs extra work and testing. Although the classification algorithm needs improvement, farmers are interested in an early introduction of the new technology. Farmers also confirm the strong preference for early detection of sick plants.

Samenvatting

Nederland is de grootste producent van gecertificeerde pootaardappelen ter wereld. In gebieden met een gematigd klimaat gelden virusziekten en bacteriële infecties (Dickeya en P. atrosepticum en P. c. subsp. Brasiliense) in het pootgoedgewas als de belangrijkste ziekten. Boeren lopen het risico dat dit hoogwaardige gewas wordt gedeclasseerd of afgekeurd en zij besteden veel moeite om zieke planten op te sporen en te verwijderen en zo te voldoen aan de inspectie-eisen van de Nederlandse Algemene Keuringsdienst (NAK).

In dit project is onderzocht of het mogelijk is om met een op vision gebaseerde AI-toepassing deze ziekten in pootaardappelen gedetecteerd kunnen worden. Het doel was om een robuust algoritme te ontwikkelen voor beide ziekten, dat kan werken onder verschillende omstandigheden (weer, bodem) en in verschillende aardappelrassen. Het doel was tevens om te testen hoe een dergelijke applicatie onder praktische omstandigheden presteert. Ook zijn de behoeften en verwachtingen in de praktijk in kaart gebracht door interactie met pootaardappelboeren en vertegenwoordigers van pootgoedhandelshuizen.

Een belangrijk onderdeel van het project betrof het ontwikkelen van een geannoteerde dataset, gedurende 4 jaar en verzameld onder verschillende weers- en bodemomstandigheden. De meeste gegevens werden verzameld op proefvelden met sterk verontreinigde variëteiten. In het laatste jaar werden ook gegevens verzameld op andere locaties dan Lelystad (Tollebeek, Valthermond). De gegevens werden geanalyseerd met het neurale netwerk EfficientnetB_0. Een model dat is getraind op gegevens van 2020-2023 resulteerde in een betrouwbaarheid van ca. 80%. Het testen van het model met verschillende subsets, gebaseerd op locatie of op verschillende variëteiten, lieten vergelijkbare betrouwbaarheidsniveau zien. Het model is ook getest op een veld met 200 verschillende rassen (NAK-locatie in Tollebeek). Het betrouwbaarheidsniveau van het model daalde naar een niveau van 74%. Dit resultaat laat zien dat een verdere verbetering van het algoritme door uitbreiding van de dataset nodig is om een goede generalisatie van het model te bereiken.

De ontwikkelingen in het project werden gedeeld met boeren en vertegenwoordigers van de pootaardappelwaardeketen. Boeren waren positief over het kwaliteitsniveau van het gepresenteerde algoritme. Ze zijn zich ervan bewust dat het creëren van een robuust vision - AI systeem extra inspanningen zal vergen. Dit geldt ook voor het kunnen voldoen aan het kwaliteitseisen van de Nederlandse Algemene Keuringsdienst (NAK). Hoewel het classificatie algoritme verbetering behoeft, zijn telers geïnteresseerd in een vroege introductie van de nieuwe technologie. Boeren bevestigen ook een sterke voorkeur voor vroegtijdige detectie van zieke planten.

1 Introduction

The Netherlands are the world's biggest producer of certified seed potatoes. In temperate climate regions, the main diseases of the seed potato crop are caused by viruses and bacterial infections (Dickeya and P. atrosepticum and P. c. subsp. Brasiliense). These two diseases are responsible for an average 14.5% declassification of seed lots (over the period 2009-2016) and an average 2.3% rejection (source: NAK - Dutch general inspection service for seeds and seed potatoes in agricultural crops). This results in a total value decrease of almost 20 million euros per year for all Dutch producers.

In order to prevent declassification, farmers put in a lot of effort to detect diseased plants and remove them before inspection by the Dutch General Inspection Service (NAK). The quality control of the potato crop (the selection) by farmers or special trained personnel is time consuming and physically demanding, in particular late in the growing season when the crop is fully developed. From KWIN data (Quantitative Information arable farming) it takes as an average 6,2hours/ha in one season, but is greatly influenced by the quality of the planting material and disease pressure in the region. The cost related to plant selection by farmers is about 8 Million euros per year (40.000ha, 6,2 hrs/ha, av. labor cost: €32,50/hr). In addition, the availability of skilled selection workers is getting more and more a problem.

In total the potential value of optimal disease detection in seed potatoes equals the cost of selection combined with the value decrease of harvested seed potatoes due to declassification. This means that there is a business model for using automated disease detection devices. In addition, the availability of skilled selection workers is getting more and more a problem. Specialized farmers that are unable to do the selection work themselves have increasing problems hiring extra selection capacity. Furthermore, human inspection is prone to false positives in which sick/diseased potato plants can be missed. This is especially the case when inspecting potato varieties with mild disease symptoms.

Reaching the right quality level of disease detection is quite challenging. Various viral pathogens result in a broad spectrum of different symptoms. Different strains of PVY have been identified that vary in symptom expression, including mosaic leaf discolorations caused by PVYO, stipple streak caused by PVYc, necrotic leaf spots caused by PVYN and PVYNTN and necrotic spots on tubers caused by PVYNTN (Verma, et. al., 2016).

Symptom expression is variety dependent. Cultivars such as Russet Norkotah and Shepody rarely show symptoms and if so, only very mild symptoms. Nevertheless, infections of these cultivars with PVY often result in a decrease in marketable yield. The symptomless infected plants can also be a reservoir for transmission by aphids.

Management of PVY is predominantly based on the use of certified, pathogen free seed, the exclusion of virus infections by removing of symptomatic plants that can serve as inoculum source, before winged aphids occur that spread the virus. In addition, sanitizing tools, planters and cultivators, weed control, in particular of solanaceous species, removal of volunteer potato plants and the use of mineral oils to reduce spread of aphids, are used in management practices. Insecticides have a low effect on the transmission of the virus, as the aphids often transmit the PVY before they are killed (Boquel, et. al., 2014). Early detection and taking out symptomatic plants is very important.

Management of bacterial diseases (like Dickeya and P. atrosepticum and P. c. subsp. Brasiliense) is mainly based on seed certification to limit the risks of using infected planting material, and on hygiene and cultivation practices that reduce cross-contamination within and between seed lots. Balanced nutrition also supports the suppressiveness of crops against these disease. The bacteria can easily spread through contaminated tubers (before and during planting) as well by man and/or machines going through the field. Also early detection to prevent the spreading is very important.

Visual crop inspections are done one to three times annually by staff of national inspection agencies. The reliability of their visual observations compared with a laboratory assay (PCR/ELISA) was found to be high (93%) for symptoms caused by viral diseases (K. Boons, NAK, unpublished results).
Precision agriculture together with computer vision technologies can be an alternative for human inspection. High tech vision solutions can mitigate the concerns from the high labor cost and increasing potato devaluation costs. If an autonomous machine can replace a human inspector and meanwhile improve the selection quality, this might provide a new business model that is based on these high-tech solutions.

Disease Detection Seed Potatoes 2015-2018
In 2015-2018 WUR Field Crops carried out a project concerning Disease Detection Seed Potatoes in collaboration with WUR Biometris. In the first year 5 techniques were explored: hyperspectral imaging, chlorophyll fluorescence, 3D, thermal camera's and finally an existing technology developed by Force-A (a French company active in the vineyards). After analyzing the potential and limitations of the techniques, both the hyperspectral imaging and 3D were selected as the most promising technologies.

In the next 3 years, first another year with lab tests was performed in order to optimize the data capturing and analysis. Potato plants in pots inoculated with viruses and Erwinia were used for this purpose.
In year 3 and 4 more practical field trials were conducted with a bigger number of plants. For this purpose a measuring device was developed capturing hyperspectral data (Specim FX10 camera) and 3D data (Ensenso).

Figure 1 *Measuring devices 2017 with 2 cameras (3D and hyperspectral).*

In all four years good results were obtained for detecting virus. Small improvements were obtained in year 3 and 4 by using Deep Learning technology. At the end the percentage of well-classified plants varied between 89 and 93%. The accuracy of detection of sick plants is better in the early stage of the selection season and at a good level of 55-63%, while the accuracy in a later stage is disappointing (34%). It seems that the wear of the leaf package in the later weeks leads to a poorer detectability of virus-sick plants.

For Erwinia the results in the first years were suboptimal. It took until the fourth year that a significant improvement was achieved by using the Deep Learning approach for data analysis. Two systems were used for this, the so-called ResNet 18 and Resnet 50. With the first, a very high percentage of the plants was scored well (95%) compared to 82% with Resnet 50. These percentages are surprisingly good. The accuracy of sick classified plants is also high (92% with Resnet 18 and 80% with Resnet 50).
In general, the algorithms scored better on virus-sick plants at the start of the season than later in the season. This seems to be related to the slow deterioration of the leaf package as it turns older.

It was recommended to work on the robustness of the detection system and also to focus on matching the detection quality with the level required by NAK quality certification requirements.

This project AGROS (2020 - 2023) builds on the results of the previous project. The more detailed approach is described in chapter 2.

2 Objectives of the project

Based on the results previous project, the partners Kubota and AgroIntelli are interested to explore the potential of a joint application that can detect diseases in seed potatoes in order to prevent declassification or rejection by the NAK (Dutch Inspection body for arable seeds). The major element of this inspection is the presence of infected plant by the PVY virus and/or the Erwinia bacterial diseases.

The following objectives are defined:

- develop a robust algorithm for both diseases, that can work under different conditions (weather, soil) and in different varieties.
- develop and optimize a technical setup for data collection:
  - supporting easy annotation based on parts of the plant with symptoms.
  - choose suitable type(s) of camera's.
  - determine if additional lighting of the camera's needed when choosing for uncovered image collection.
- test the algorithms under practical conditions.
- discuss with farmers on expectations and practical value of automated classification.

The focus in this project is on the disease detection itself, using AI. The automated removal of sick plants, which obligatory in practise, is out-of-scope.

3 Experimental setup

3.1 Field preparation and inoculation test

The data of the infected and healthy potatoes were collected at the experimental fields of Wageningen University & Research Field Crops in Lelystad. The field were partly planted with batches of tubers with a relatively high level of virus infection, partly with tubers that were inoculated with Erwinia. Figure 2 shows a picture of the field. In ANNEX 1 an example of the field layout (year) is presented.

From 2021 to 2023 tubers from 6 varieties were inoculated to create a fair level of Erwinia sick plants. In 2021 and 2022 it was measured what the effect of inoculant was on the total amount sick plants per variety in the test field. They were divided in four groups with each a different Pectobacteriaceae variety and water, to check the effect of the different varieties and how the plants reacted.

Figure 2 *Picture of experimental field in Lelystad (2022).*

Tables 1 and 2 displays the total infections per variety for all bacterial varieties. In the field we also noticed that on average the water inoculated plants grew larger than both the bacterial inoculated with and without symptoms. In 2021, all varieties were inoculated with CFU (colony forming units) 10E6 ml–1. This amount of inoculum is similar to those employed in other studies (van der Wolf et al., 2017; de Haan et al., 2008). In 2022, it was decided to decrease the inoculation concentration with a factor of 10 to CFU 10E5 ml–1 for the variety Agria, Esmee, Fontane, and Riviera. It was expected that with a lower amount of inoculation, the potato plants would show less severe symptoms. Both Kuras and Kuroda were still treated with CFU 10E6 ml –1 since Table 1 suggests that these varieties were less sensitive for showing symptoms. Since the distribution between sick and healthy plants was good for recording, it was decided to keep similar inoculant for 2023 (expert opinion).

Table 1 *Total number of blackleg situations where visual symptoms were observed in the field at the last data collection moment in 2021. Each potato variety Pectobacteriaceae combination contained 250 infected tubers*.

Variety	*D. solani*	*P. atrosepticum*	*P. brasiliense*	water
Agria	55/250	89/250	125/250	57/500
Esmee	95/250	116/250	156/250	0/500
Fontane	93/250	100/250	155/250	0/500
Kuras	5/250	7/250	11/250	0/500
Kuroda	25/250	30/250	18/250	0/500
Riviera	16/250	29/250	83/250	0/500

Table 2 *Number of blackleg situations where visual symptoms were observed in the field at the last datcollection moment in 2022. Each potato variety Pectobacteriaceae combination contained 250 infected tubers.*

Variety	*D. solani*	*P. atrosepticum*	*P. brasiliense*	water
Agria	14/250	54/250	82/250	1/500
Esmee	57/250	38/250	100/250	0/500
Fontane	36/250	83/250	159/250	0/500
Kuras	6/250	32/250	50/250	1/500
Kuroda	15/250	37/250	36/250	1/500
Riviera	12/250	58/250	166/250	2/500

3.2 Data collection in the field

The potato image data was collected on two platforms. In 2021 the data was collected on a self-constructed manual carrier with 2 side cameras and in 2022 and 2023 with a modified selection cart. On the front of the selection cart a hydraulic arm was built where three camera systems were placed (3x IDS camera GV-5280FA-C-HW with RICOH FL-CC0814-5M 8mm lenses). In addition four led lights were installed (7400 lumens per light) to reduce the effect of the shadow. A GPS antenna (Emlid Reach RS2+) was installed centered above the middle camera to capture the exact position of the potato plants. In 2021 the setup started with 2 cameras tilted to look to the side-top view of the potato plants, and this was altered to three cameras in 2023 with a top view, and two from the side. The camera trigger was based on a manual button on a touchscreen or an automatic trigger based on distance. In the use case of sick potatoes, the trigger was set to take a photo each 0.1m. During the season an inspector from the NAK was hired to identify the sick potato fields and mark them with colored sticks. These sticks were manually removed by the operator of the data collection system when an image of the potato was taken.

(a) (b)

Figure 3 *The selection cart (3a) equipped with sensors and the visible colored sticks (3b) for data collection: A: Emlid reach RTK gps antenna, B: Xsense IMU (not used), C: IDS camera lens D: Matronics led lights, and E: touchscreen PC.*

3.3 Creating datasets for evaluation

The base dataset consists of a very large set of images with metadata such as acquisition time and GPS coordinates. The data are available for the years 2017, 2018, 2020, 2021, 2022, and 2023. There were differences across the years with respect to cameras used, camera orientation, and folder structure. Subsets of these data were selected using a Python script that looks up coordinates of sick plants and locates the images corresponding to their locations, along with healthy plants. Other information such as site or variety was also obtained from the records of GPS coordinates. This way, a global catalogue of 41 thousand images across the years was selected, containing images from all these years and other criteria. From this database, it is possible to filter images corresponding to a particular year or variety.

Table 3 *Number of images selected per year and annotated by label (2017-2023).*

Year	Healthy	Sick	Varieties in the dataset	
2017	250	670	Kondor, Rosa Gold, Lady Clair, Vermont, PCR/11	Roze Gold, Lady Claire, Vermont
2018	528	500	Kondor, Rosa Gold, Lady Clair, Vermont, PCR/11	Ditta, Festien
2020	3993	2055	Agria, Esmee, Fontane, Kuras, Kuroda, and Riviera	(n/a)
2021*	1726	5650	Agria, Bintje, Esmee, Fontane, Innovator, Kuras, Kuroda, and Riviera	Bintje, Innovator
2022	16178	9632	Agria, Esmee, Fontane, Kuras, Kuroda, Natural, Riviera, Mozart, Agria, Vogue	Bintje, Innovator
2023	5334	2954	**Lelystad**: Esmee, Fontane, Kuroda **Tollebeek**: 200+ varieties **Valthermond:** TBM	Jacky, Kartel

*** *unbalanced dataset due to rejection of healthy plants being rejected by having too many sick plants***

In all experiments, a split of 60% for training, 20 % for validation, and 20 % for testing was used. There were in most cases (an exception being the year 2021), twice as many healthy images as sick ones. The catalogue was also populated with the percentage of green pixels in each image and the criteria for deciding the contrast.

3.4 Methodology

Since the classification problem involves assigning an image level label (healthy or sick), the EfficientnetB_0 classifier, for which a previous version of the code was available, was used. Classification based on ResNet18 was also attempted but was found to be much slower. To build a classifier model for a particular condition, the following steps were followed: (i) pre select images from the catalogue (for example, by year, variety, location, etc), (ii) build the train/val/test folder structure with these images, (iii) train the model, (iv) apply the trained model on the test set and assess the performance.

The first step was to pre-process the images to remove the images that didn’t contain potato plant information, due to gaps with no plants in the rows, and stopping the recording too late. To discard images without any plants, the chromaticity transform was applied on each RGB image and a threshold was applied on the normalized green - (red+blue) to get a pixel wise classification of green or non-green. This way, images with very few green pixels can be discarded. In figure 4 an example is presented.

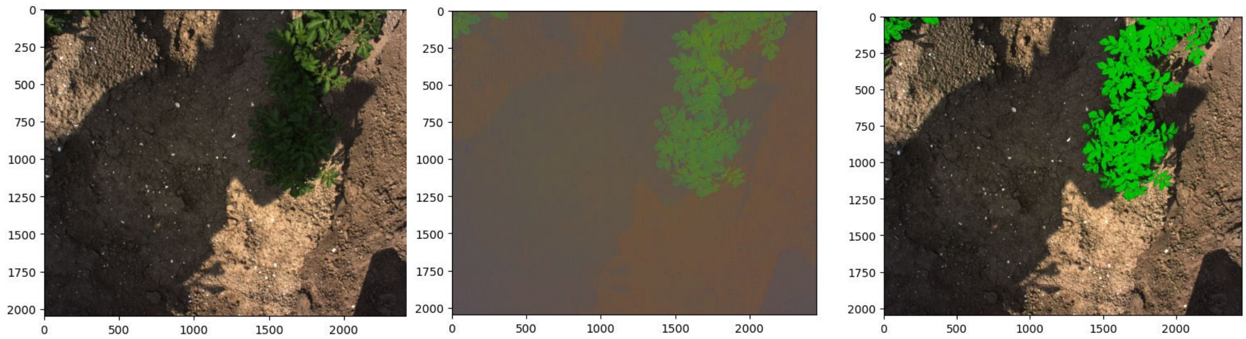

Figure 4 *Example of chromaticity transform applied on an image with a limited amount of green pixels.*

When selecting the healthy potato plant images for our dataset, all images were left out that were taken within a radius of 1.5m around the potato plant showing symptoms of blackleg. In total a two-fold of healthy plants were selected compared to sick plants. This however also caused the imbalance in sick and healthy plants in the 2021 dataset, as in this year almost all of the plants became sick.

4 Results

In this chapter, the results of different actions are presented. Most of the presented results are based on the data analysis of the complete dataset available at the end of 2023 (except par. 4.1). Presentation of results of intermediate data analysis in the intermediate years is not considered to be of added value.

In the next paragraphs, in par. 4.1 the results of a comparison of different image classifiers based on data of 2021 will be presented. In par. 4.2 the results are presented when training the "best performing algorithm" with all data and test it different subsets per location of the trials (Tollebeek (NAK), Valthermond, Lelystad). This provides good insights on the generalizability of the algorithm. In par. 4.3 the focus is on the effect of direct sunlight on the classification results. Finally in par. 4.4 the first results of a trial to improve early detection are shared.

Since the classification problem involves assigning an classification label at plant level of being healthy or sick, the EfficientnetB_0 classifier implemented in PyTorch was used.

4.1 Comparison of different image classifiers based on data of 2021.

The fast developments in AI triggered the need to make a comparison of different classifier tools and versions and test their quality in terms of Recall and Precision (as well as combined in the F1 score). The training set was based on 7375 images of the season 2021. Table 4 shows the results of both different versions of EfficientnetV2 and Resnet, all trained and tested on exactly the same data sets. In general, the EfficientnetV2 network performed better than Resnet. The best performing EfficientnetV2 showed an the F1 of 4,4% higher than the best performing Resnet network.

Table 4 *Classification performance of different classifiers (and versions), trained and tested on the 2021 dataset.*

A	B	D	E	F	G	H	N	O	P	Q	R	S	T	U
Network	learning rate	Trained epochs	Dropout	Data Augmentation	ImgSize	Dataset	HH	HV	VH	VV	Accuracy	Precision	Recall	F1
efficientnetv2-xl-21k	1,00E-04	150	0,2	TRUE	512	Tensorflow2	138	5	8	135	95,5%	96,4%	94,4%	95,4%
efficientnetv2-s-21k	1,00E-04	150	0,2	TRUE	512	Tensorflow2	134	9	7	136	94,4%	93,8%	95,1%	94,4%
efficientnetB3	1,00E-04	150	0,2	TRUE	512	Tensorflow2	130	13	4	139	94,1%	91,4%	97,2%	94,2%
efficientnetB7	1,00E-07	200	0,2	TRUE	600	Tensorflow2	132	11	7	136	93,7%	92,5%	95,1%	93,8%
efficientnetv2-xl-21k-nogwat	1,00E-07	71	0,2	TRUE	512	Tensorflow2	133	10	8	135	93,7%	93,1%	94,4%	93,8%
Resnet50_7	5,00E-05	200	0,1	FALSE	1280	Resnet2	135	8	17	126	91,3%	94,0%	88,1%	91,0%
efficientnetv2-xl-21k	1,00E-07	200	0,2	TRUE	224	Tensorflow2	135	8	18	125	90,9%	94,0%	87,4%	90,6%
efficientnetB0	1,00E-07	200	0,2	TRUE	600	Tensorflow2	130	13	17	126	89,5%	90,6%	88,1%	89,4%
Resnet152_4	1,00E-06	200	0,2	FALSE	1280	Resnet2	127	16	15	128	89,2%	88,9%	89,5%	89,2%
Resnet18	1,00E-04	200	0,01	FALSE	1280	Resnet2	136	7	26	117	88,5%	94,4%	81,8%	87,6%
Resnet152_6	1,00E-06	200	0,35	FALSE	1280	Resnet2	134	9	28	115	87,1%	92,7%	80,4%	86,1%
Resnet50	5,00E-05	200	0,15	TRUE	512	Tensorflow2	136	7	31	112	86,7%	94,1%	78,3%	85,5%
Resnet50	5,00E-05	200	0,2	TRUE	1280	Resnet1	210	4	47	96	85,7%	96,0%	67,1%	79,0%
Resnet50	5,00E-05	200	0,2	FALSE	1280	Resnet1	189	25	30	113	84,6%	81,9%	79,0%	80,4%
Resnet50_7	5,00E-05	200	0,1	TRUE	512	Resnet2	135	8	37	106	84,3%	93,0%	74,1%	82,5%
Resnet50	5,00E-05	200	0,2	TRUE	1280	Resnet2	136	7	41	102	83,2%	93,6%	71,3%	81,0%
Resnet50_7	5,00E-05	200	0,1	FALSE	512	Resnet2	130	13	37	106	82,5%	89,1%	74,1%	80,9%
Resnet50	1,00E-05	200	0,2	FALSE	1280	Resnet2	137	6	47	96	81,5%	94,1%	67,1%	78,4%
Resnet18	1,00E-04	200	0,01	TRUE	1280	Resnet2	131	12	47	96	79,4%	88,9%	67,1%	76,5%
Resnet152_3	1,00E-07	200	0,2	FALSE	1280	Resnet2	118	25	40	103	77,3%	80,5%	72,0%	76,0%
Resnet152_5	1,00E-07	200	0,75	FALSE	1280	Resnet2	115	28	38	105	76,9%	78,9%	73,4%	76,1%
Resnet50	5,00E-05	200	0,2	FALSE	224	Resnet1	187	27	65	78	74,2%	74,3%	54,5%	62,9%
Resnet18	1,00E-04	200	0,01	FALSE	224	Resnet2	111	32	45	98	73,1%	75,4%	68,5%	71,8%

4.2 Results of the best performing algorithm

In each of the experiments, the relevant images are selected from the catalogue and the model is trained. For evaluating the performance of the classification, a confusion matrix is computed knowing the ground truth labels of the test set and the respective predicted labels. This allows to get an idea of the overall accuracy as well as the number of misclassifications.

This global model was trained on images from the years 2020 until 2023. The first model performed fairly well on the test set with an accuracy of 79% (see Figure 5). Of the healthy plants 90,2% was well classified (9,8% FN).

When including images of 2017 and 2018 (having a different camera and shielded setup) the number of misclassifications of sick plants increased (from 34,3% to 51,3%), while the number of false positives decreased from 9,8 to 7,7%.

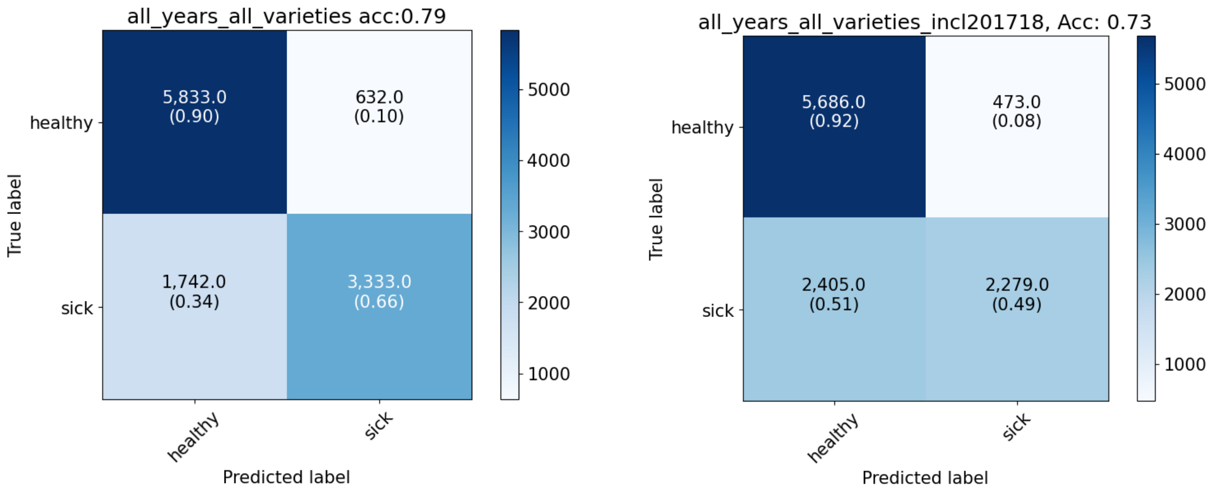

Figure 5 *Confusion matrix of model trained from 2020 to 2023 (left), including 2017 and 2018 (right).*

Generalizability
The generalizability of this model was evaluated by testing it on a breakdown of the dataset, according to year, location, and variety (only tested on 1 variety). Figure 6 shows the results of models trained on 6 different training sets and tested on 6 test sets.

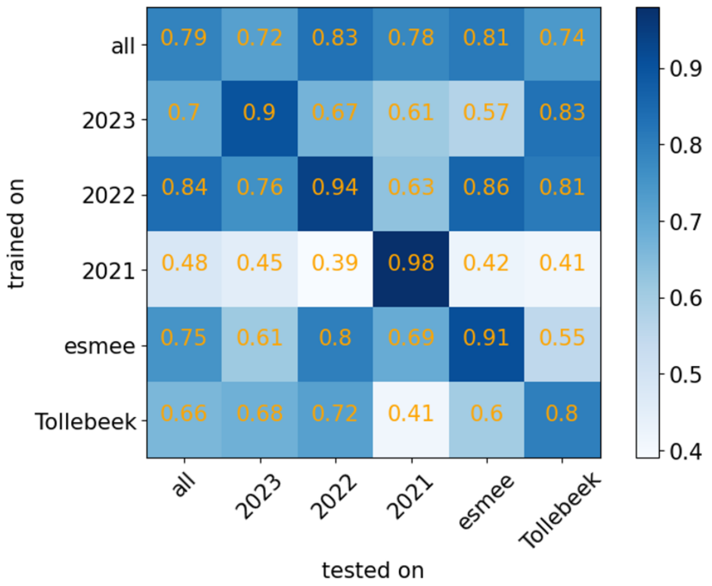

Figure 6 *Overall accuracy matrix of results when training 6 different models on 6 different test sets.*

The model trained on only 2022 data shows a better performance than the global model (trained on data of 2020-2023). The model trained on data of 2021 is performing very poor. This is probably due to an imbalanced dataset with many sick plants compared to the healthy ones.
The combination of 4 years data performs a bit worse than data from only 2022. It seems that this might be due to dataset of 2021. Moreover, in 2021 only the angled camera orientations were available, unlike the top view as well as the angled views in the other years. As a check, by excluding the 2021 images and training the model only on the images from 2020, 2022, and 2023, it was found that the resulting model accuracy increased significantly from 0.79 to 0.86 as shown in the confusion matrix in figure 7. The overall accuracy improved from 79 to 86%, a significant improvement.

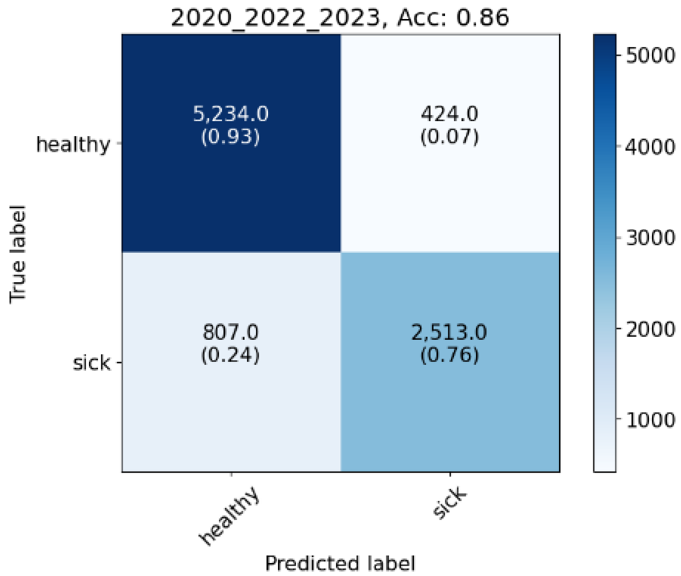

Figure 7 *Confusion matrix of model trained with dataset 2020, 2022 and 2023 and tested on all data.*

<u>Yearly Models</u>
For the years 2023, 2022 and 2021, combined, specific models were trained on the images from the respective years. It can be seen from the confusion matrices that year specific models perform better on their year's test sets.

The accuracy as shown in figure 8, is specified per year in Figure 9 - 10

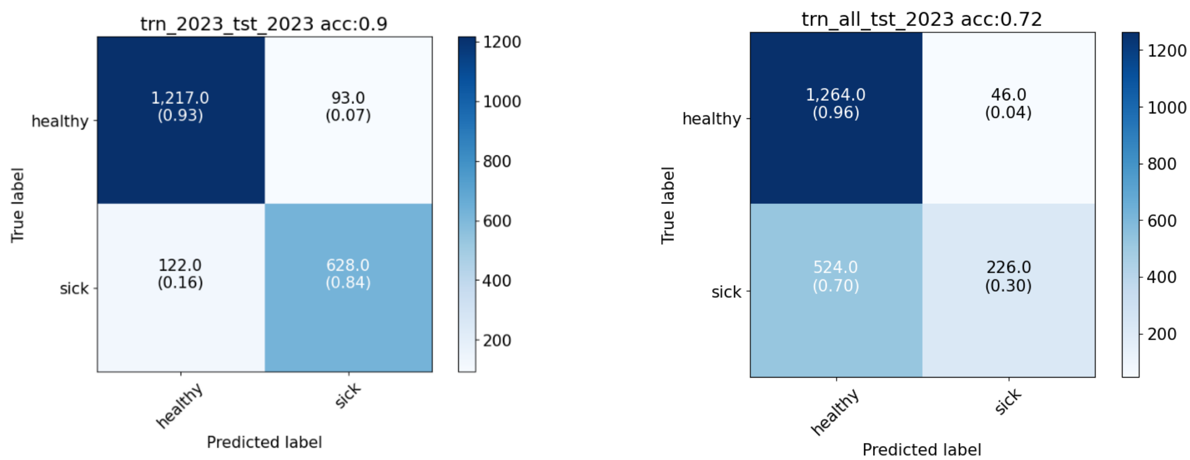

Figure 8 *Confusion matrix for year specific model 2023 (left) and for global model applied on the 2023 test set (right).*

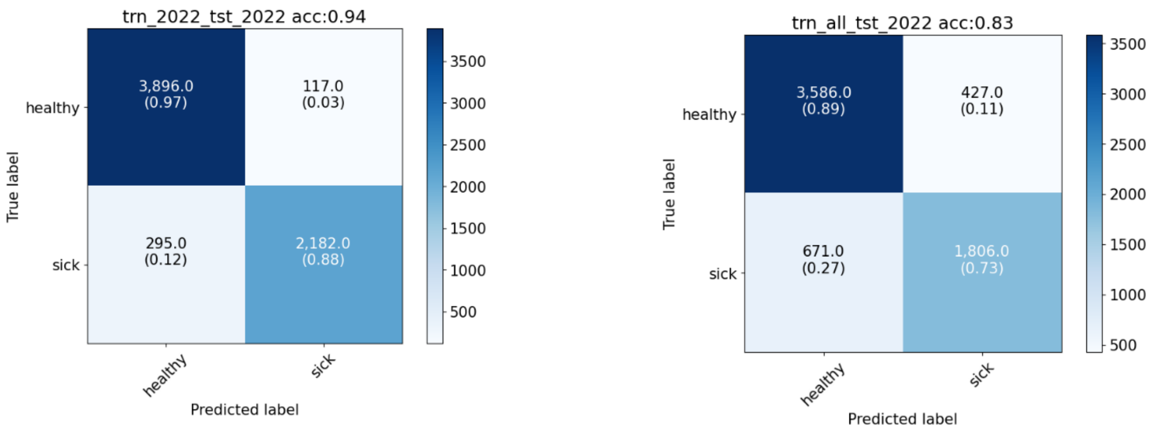

Figure 9 *Confusion matrix for year specific model 2022 (left) and for global model applied on the 2022 test set (right).*

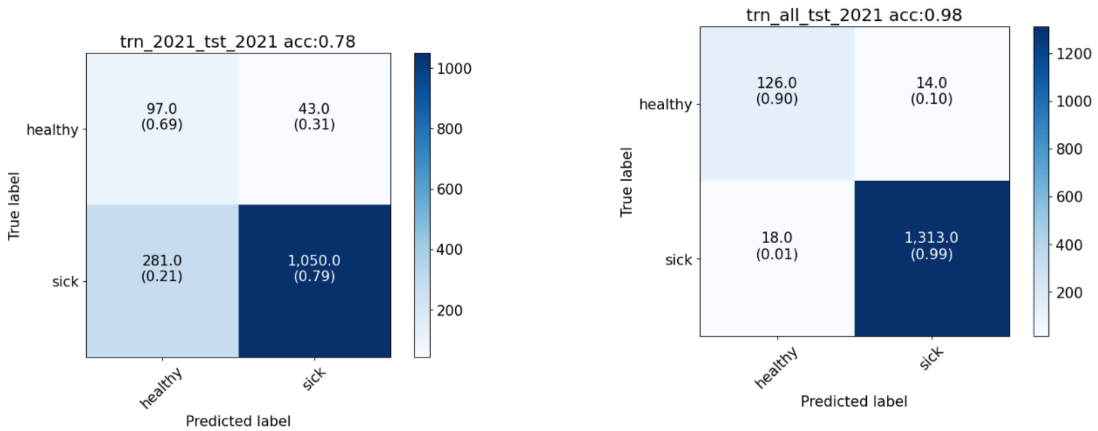

Figure 10 *Confusion matrix for year specific model 2021 (left) and for global model applied on the 2021 test set (right).*

From these analyses can be concluded that there is quite a big difference in the precision between training and testing on year-specific data and testing the global model on the same year-specific test set. These results also show that the dataset of 2021 is out-of-balance. This is caused by a script that excluded healthy plants that grow in the direct neighbourhood of a sick plant. By excluding the 2021 data from the training dataset the accuracy improved significantly from 79% to 86%.
The 2022 dataset seems to generalize well for other years compared to most of the other datasets.

4.3 Trained by contrast setting

Experts in potato disease selection have experienced that direct sunlight is challenging for finding sick plants, especially virus infected plants. During data collection in this project direct sunlight created a high contrast, resulting in low visibility of leaves a bit deeper in the crop foliage. The strong LED lights connected to the camera setup is not able to sufficiently compensate the contrast created by the direct sunlight. A solution for this is shading the foliage with a white and transparent cover above the cameras. To get an impression of the effect, the dataset is split into subset collected under shaded conditions.

For deciding whether an image has good or bad contrast, the HSV (Hue Saturation Value) transform of the image is computed, followed by the ratios “hue to intensity” value and “saturation to intensity” value. The means and variances of these two ratios are calculated. An image is considered as having a good contrast if its variances are below a threshold, else it is considered as having a bad contrast. These thresholds were selected empirically by applying them on a manually selected set of good and bad contrast images. Examples of good and bad contrast are show in Figure 11.

Figure 11 *Images with good contrast (above) and bad contrast (below).*

Based on the statistical criteria for image contrast described in the previous section, images from the years 2020 until and including 2023 were split into two groups with good or bad contrast, and two models were trained on their respective images. The confusion matrices over the two test sets are shown in Figure 12.

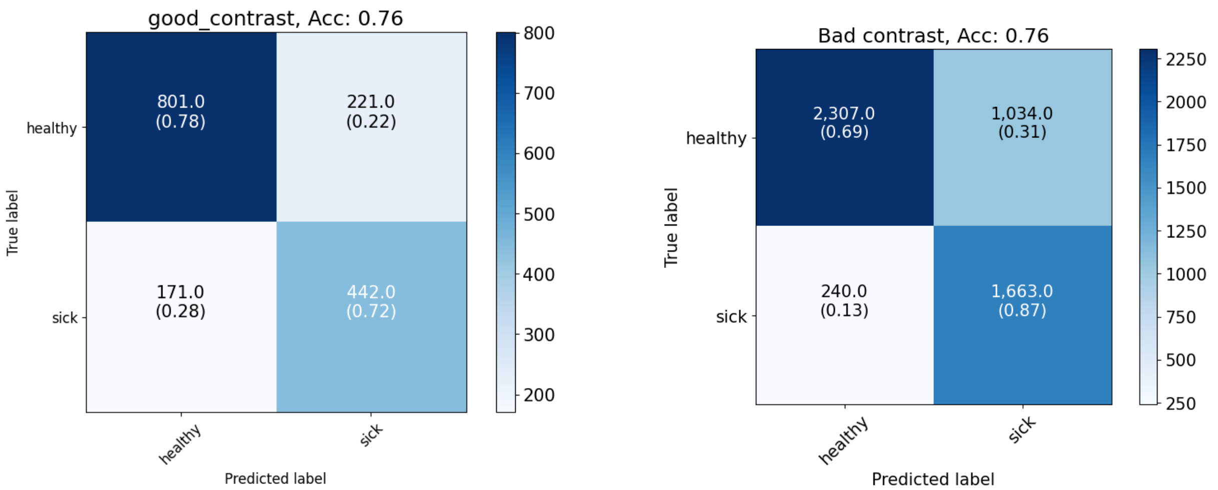

Figure 12 *Confusion matrices based on a split dataset of years 2020-2023 with a "good" contrast (left) and a "bad" contrast (right).*

These results show a comparable accuracy in both cases. An explanation can be the non-uniform dataset sizes. The healthy to sick misclassifications (False Positive) is better when the contrast is good (21% versus 31%). Although these results are not conclusive, it is recommended to work on creating a good level of contrast, either by combining the current LED light-camera setup with a sun cover or use a flash light-camera setup.

4.4 Trained by location

For the year 2023, image acquisitions was done at different locations, namely, Lelystad (production field – planting distance 18cm), Lelystad (demo field – planting distance 33cm), Valthermond (peaty soil), and Tollebeek (clay soil). To study the effect of the location, i.e., how well a model generalizes across locations, the images from 2023 were filtered by location and location specific models were trained. For evaluation, the confusion matrices were computed for each model and its respective location's test set, and the models were also applied across locations and the resulting accuracies were compared. The results are shown in Figure 13 - 14.

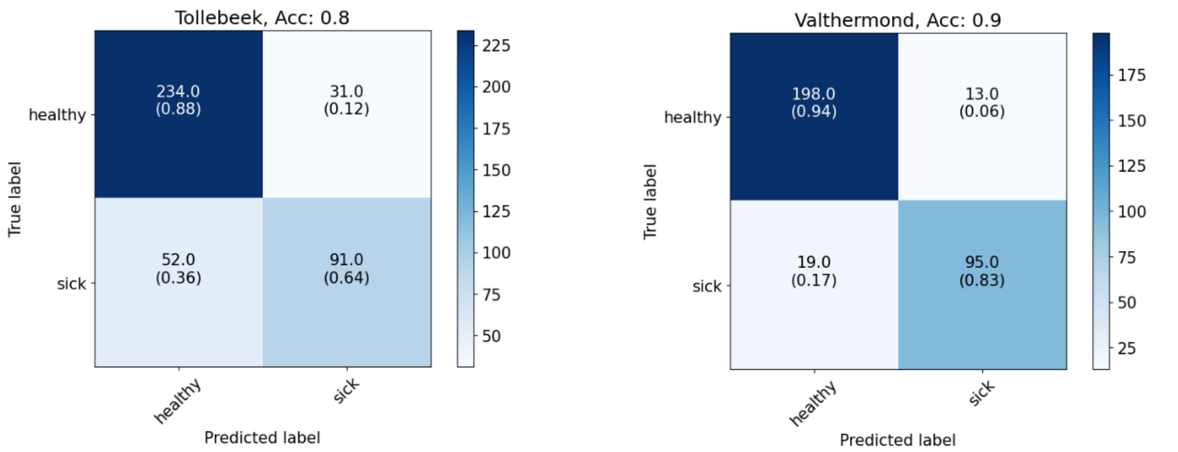

Figure 13 *Confusion matrices of testing the location specific models on two location specific test sets, Tollebeek (left) and Valthermond (right)*

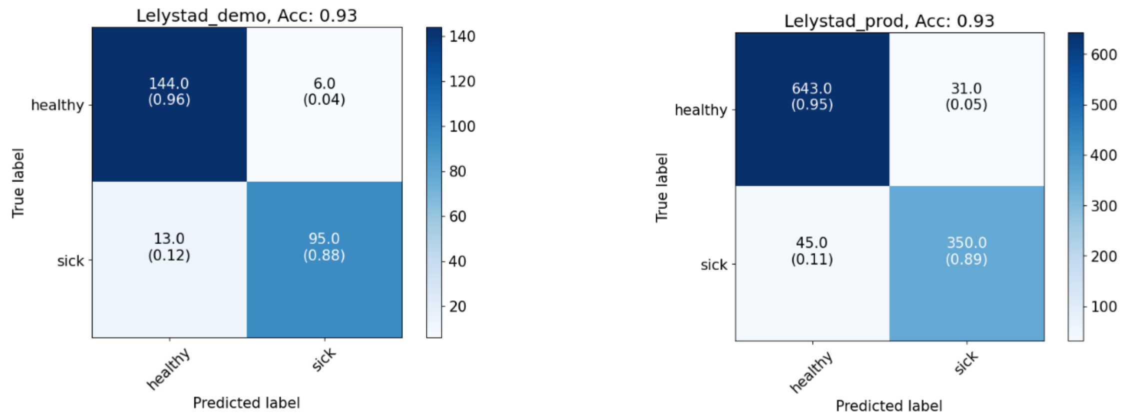

Figure 14 *Confusion matrices of testing the global model on two location specific test sets, Lelystad demo field (left) and Lelystad production field (right)*

The overall matrix is showing the accuracies obtained by applying a model trained on 2023 data and applied on test sets of the different locations (see Figure 15). Each row corresponds to a trained model and each column to a test set. This way, we can compare the performance of a location specific model in a test scenario from a different location.

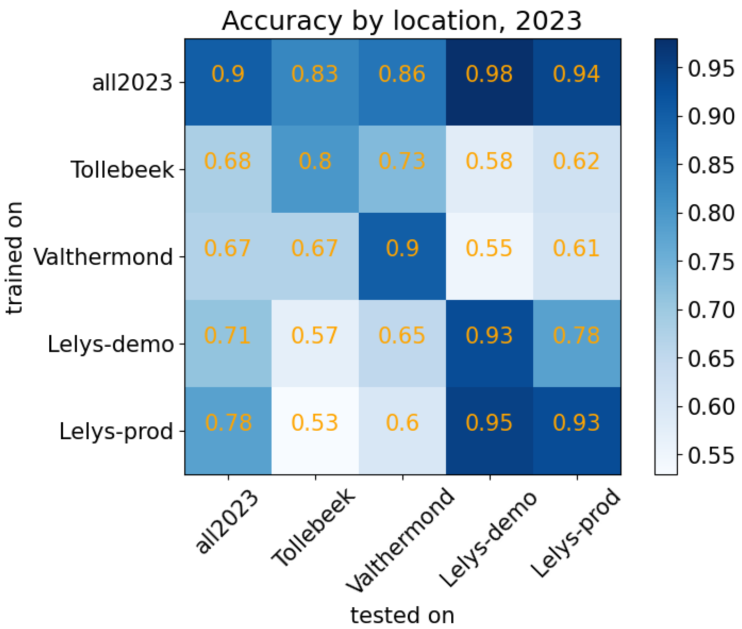

Figure 15 *Overall accuracy matrix of results when training 5 different location based models (including a model trained on all locations) on 5 different test sets.*

As can be expected, the best performance is found when a model is trained and tested for a specific location, although the global 2023 model is performing close to that level. The 2023 global model (trained on all 2023 data) performs fairly good when tested on the different locations. Especially the accuracy scores of the locations Tollebeek and Valthermond are still quite good, while the first location contains data of 200 different varieties and the growing circumstances (soil type) in Valthermond differ strongly from the situation in both Lelystad and Tollebeek.
On the other hand, models trained on only data from Tollebeek and/or Valthermond don't perform well on other locations. The basis of these location specific models is too small.

4.5 Additional cameras

In order to be able to detect disease symptoms deeper in the canopy, the data acquisition platform was equipped with 3 cameras. In the previous part of the analysis (par. 4.1-4.4) only the central top view camera (#3) was used. The other two cameras 1 and 2 were place in an angle of about 30º (see also chapter 3). The objective of the analysis is to get a first impression of the added value of using the 3 cameras for classification.

The 2022 dataset of the top view camera (#3) and its trained model was considered as the baseline. The respective images for cameras 1 and 2 were linked by using the closest time stamp and sequence number to those of the top view camera images. The same train/validate/test splits as for camera 3 were used. First, for each camera, a model was trained using its images and a confusion matrix was computed on its test set.

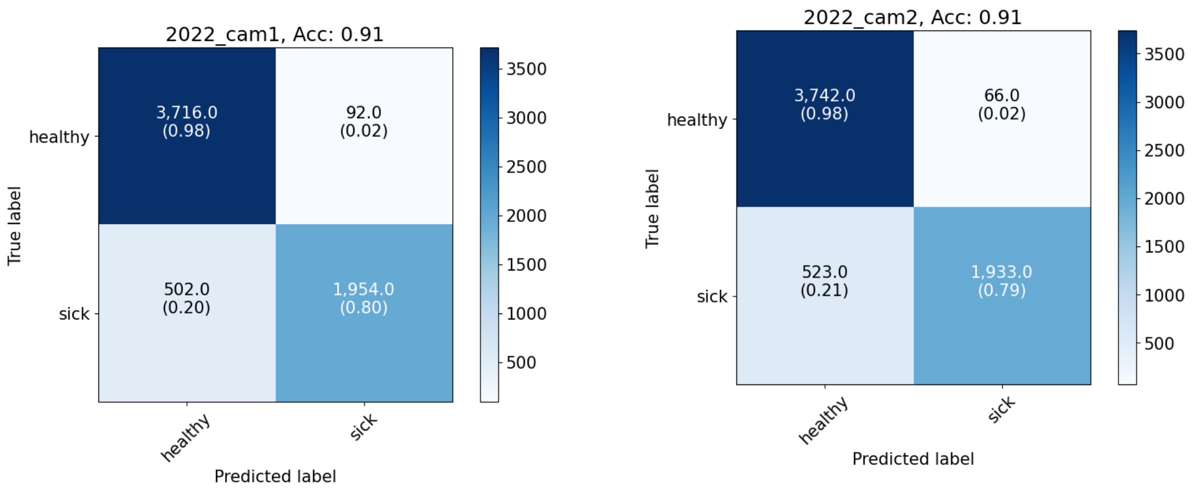

Figure 16 *Confusion matrix for camera 1 (left) and camera 2 (right) with model trained on 2023 top view camera data and tested on datasets of both cameras.*

To integrate the results of all 3 cameras, a majority voting approach over the results of the 3 models over the respective images for each plant was implemented. This means that first the classification of all three cameras was done, followed by a final classification based majority voting (the outcome of 2 out of 3). In Figure 17 the confusion matrix is shown.

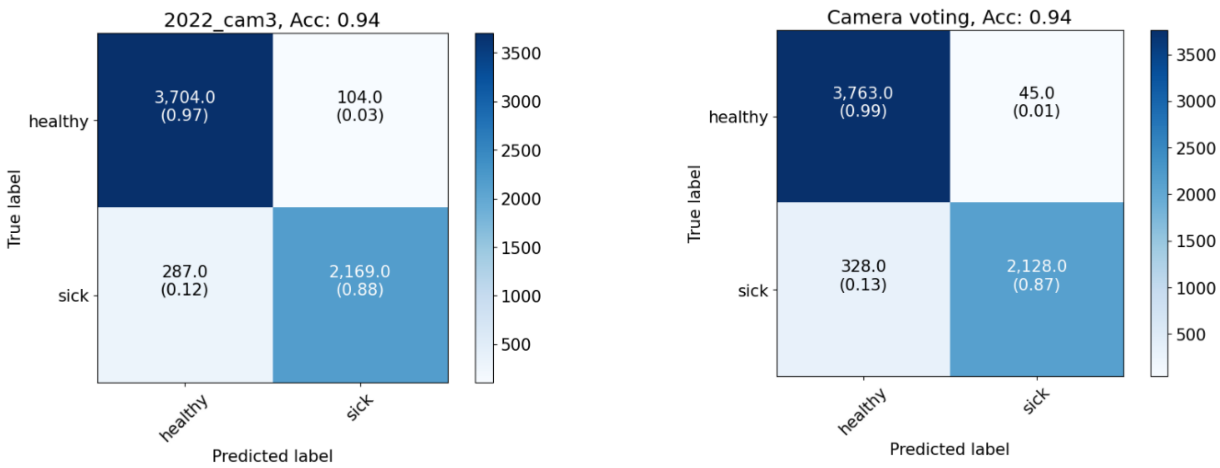

Figure 17 *Confusion matrix for the top view camera 3 (left) trained on only the top view 2023 data set and for outcome by majority voting (right) over all 3 cameras (trained and tested on the dataset of that specific camera).*

As first conclusions the confusion matrices show that:

- Individually, cameras 1 and 2 tend to misclassify more sick plants as healthy, compared to the top view camera #3.
- Incorporating the additional cameras through voting leads to fewer healthy to sick misclassifications compared to using camera 3 alone, but otherwise similar accuracy and other metrics.

Other classifying mechanisms than majority voting could be more successful but need additional research. Additional data collection and analysis on more diverse data set is needed to really draw conclusions.

4.6 Heatmaps / Grad-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM) is a tool used to understand how deep learning models produce their predictions for a particular class (Selvaraju et al., 2017), based on generated "visual explanations." It was developed for localising class-discriminative regions used by Convolutional Neural Networks (CNNs) in tasks such as image classification. This tool was used to visualize the regions that a CNN focuses on when classifying an image containing multiple potato plants. Since symptoms of bacterial infections can be subtle the Grad-CAM tool provides insights into the decision-making process of the model.

Grad-CAM calculates the gradient weights of the last convolutional layer in a model, as this layer represents the final gradients used to make the prediction and provides the most explanatory value. When the gradient is low, or there is no focus, the colour will be a very light blue, when there is more focus the colour moves from yellow to red, which indicates the most important pixels. The colour map is then overlaid on the original input image, showcasing the regions where the algorithm had the most focus. In Figure 18 an example is presented of a sick plant: the red parts are the most relevant parts for the classification of the plant being sick. This tool also helps by adding localisation information over the already existing classification information.

Figuur 18 *Example of Grad-CAM output of sick potato plant (left) and the original picture (right).*

4.7 Field demo (July 2023)

On the 7th of July 2023 a demo of the algorithms was presented to a group of interested people, consisting of six farmers and representatives of seed potato companies, advisory services and machine producers. The objective was to share the progress made in detection using AI and to discuss the potential of such an application, the quality needed and how the implementation of a robot type of solution could look like.

After a presentation of the projects objectives and an in-field demonstration, the major feedback of the group present can be summarized by theme.

<u>Quality of the output</u>: how good should the quality be when starting?

- Farmers confirm the lack of qualified personnel for the selection process.
- Some farmers have experience with AI applications for sorting potatoes. They have experienced that the performance can best be improved by starting to use the application under practical conditions. Their plea was to speed up the development of disease detection robot for seed potatoes and start testing under practical conditions on farms. Farmers don't mind to send unqualified personnel in the fields to take marked sick plants out in the first period.

- Early detection of the sick plants is very important for farmers. Prevention of contamination of surrounding plants is very important. An algorithm that is able to detect sick plants when they are still small, will be a big advantage. Suggested is to pay extra attention to the plants that are considered to be healthy but having a confidence level that is close to the threshold.
- Farmers prefer to have on option that enables them to change the confidence threshold to have influence on the level of false negatives and false positives. A farmer may want to choose a different threshold depending on the quality grade of the seed potato per field.
- Farmers suggested to create different model per different stages of the plant growth. Another option could be to have different models per group of varieties. For now, the focus is on maximising the generalization of the trained model.

Robot solution

- Number of cameras per plant: it's not clear what the added value is of an additional set of 2 camera's. Looking at a plant under an angle (e.g. 30%) might improve the performance of the algorithm.
- Lighting of the plant: the current set op LED lights per camera could be exchanged for flashlight. Flashlight has a 5x times higher intensity than LED light and uses less energy.
- A robot solution running on small tracks (e.g. max 15cm) is attractive to operate smoothly under difficult circumstances. There are already successful track type selection carts available on the market.

Other:

- Farmers would like to know if the performance of the algorithm is influenced by wet leaves (rain, dew). This has not yet been tested.
- The same question regarding the use of mineral oil. The current experimental fields were treated like a normal field in practice, so also mineral oil was used on regular basis. The use of mineral oil is taken into account in the precision rates.
- Business model: the level of investment in a robot solution like this is correlated with the number of hectares per machine in a season. The working speed of a machine will probably be around 1 – 1,5m/sec. When a machines can successfully control the disease level and/or performs better that the human eye, the return on investment will even improve.

Conclusion:

Besides technical questions and suggestions, the bottom-line of the demonstration and discussion session was not to wait till a perfect generalized algorithm has been developed. Farmers are willing to invest time to improve a system in order to speed up a successful implementation in practice.

5 Conclusions

After 4 years of data collection in mainly experimental fields with sick plants (virus and Erwinia) a fair to good performing algorithm has been developed. The confusion matrices of the so called global model (trained on data of the 4 year) tested on different subsets (per year and per location) show a precision of around 80%. A model trained on only the 2022 dataset performs slightly better in terms of precision when tested on the different subsets. This dataset turns out to be very representative for different field settings and the model leads to a better generalization. The exclusion of 2021 data in the training dataset leads to a improved accuracy of 86% (was 79% with the 2021 dataset included).

The global model seems to generalize at about the same quality level. Testing the model with different subsets, based on location or on different varieties show a similar level of precision. The best test use case was the one done at the NAK location in Tollebeek on a field with 200 different varieties in small plots. The precision level of the global model dropped to a level of 74%. This result shows that the generalization is not yet at the requested level.

As can be expected, a model trained on a specific subset (year, location) performs better on a test set linked to that specific subset.

Collecting data under more controlled circumstances (by covering the plants in order to create a better dataset with good contrast) doesn't show a significant better performance of the model. Additional research is needed.

A first comparison between the model's performance when using only the top view camera or using a combination of the top view camera and 2 cameras looking at the plant under a 30degree angle, show similar results when based on majority voting system. Additional research is needed to test different decision making system.

On demonstration event in July 2023 intensive discussions with farmers and representatives of seed potato value chain took place. Farmers were positive about the quality level of the algorithm presented. They are aware that creating a robust AI algorithm will take time. Even though the classification algorithm needs improvement to meet the quality level used by the Dutch General Inspection Service (NAK) , but are interested in an early introduction of the new technology. Farmers confirm the need for early detection of sick plants.

5.1 Discussion - recommendations

Quality level

The inspection of seed potato fields by the Dutch General Inspection Service (NAK) is based on strict norms. The confusion matrices show a level of accuracy of around 80%, based on a test set that consists of annotated data of a complete season. In practice, a farmer inspects his field usually 3 to 6 times per season and removes sick plants every time. At the end of the season, he is able to take out almost 100% of the sick plants. Also a future robot solution will do several runs in a season. Additionally, we don't know yet how the precision level of the model relates to the quality level of the Inspection service by NAK. We expect, based on the expert opinion that it should be at about 95%. According to the inspection norms that apply here, the number of False Negative (sick plants that are classified as healthy) should be quite low to prevent declassification of the field. Relevant in this case it the fact that the robotized solution will go through the field at least 3-4 times per season. Also the cumulative effect of the multi passes is not yet tested.

Generalization

In the project most data is collected in the research location of WUR Field crops in Lelystad. In the period of 4 years different weather conditions created a variety of growing conditions with more or less crop foliage. Only in the 4th year different location in other regions were included. During the years different varieties were present in the dataset. It is preferred to work towards one general algorithm for all varieties and all regions. Besides improving the accuracy of the classification algorithm, which still seems necessary, it is worthwhile to investigate if region specific algorithms result in improved accuracy. Related to varieties, it is important in future research to make sure that the algorithm performs well on the top-10 most important varieties.

Early detection

Another important element is the timeliness of detection. Both diseases easily spread through the field. Early detection is therefore crucial for a successful application. Improving early detection will require research on other technologies like a combination of hyperspectral cameras and AI. Also timeline analysis of datasets might help finding symptoms in an early stage.

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Annex 1 Overview test field 2022

Erw 1 _ Dickeya solani IPO2222 met groene labels
Erw 2 _ Pectobacterium atrosepticum IPO1007 met witte labels
Erw 3 _ P. brasiliense IPO3649 met gele labels
WATER
Virus makkelijk
Virus moeilijk
Erwinia Mozart (natuurlijk) (partij 1 hzpc)
Agria/vogue natuurlijk
Fontane (natuurlijk)

	Spuitspoor			
rij 28	Virus Moeilijk			Pootafstand 0,5M
rij 27	Virus Moeilijk			
rij 26	Virus Moeilijk			
rij 25	Virus Moeilijk			
rij 24	Virus Moeilijk			
rij 23	Virus Moeilijk			
rij 22	Virus Makkelijk			
rij 21	Virus Makkelijk			
rij 20	Virus Makkelijk			
rij 19	Virus Makkelijk			
rij 18	Virus Makkelijk			
rij 17	Virus Makkelijk			
rij 16	Virus Makkelijk			
rij 15	Virus Makkelijk			
rij 14				
rij 13				
rij 12	Fontane NH (natuurlijk)	Fontane Texel (natuurlijk)	Partij3	Pootafstand conform praktijk
rij 11	Fontane NH (natuurlijk)	Fontane Texel (natuurlijk)		
rij 10	Fontane NH (natuurlijk)	Fontane Texel (natuurlijk)		
rij 9	Fontane NH (natuurlijk)	Fontane Texel (natuurlijk)		
rij 8	Vogue natuurlijk	Agria natuurlijk	Partij2	
rij 7	Vogue natuurlijk	Agria natuurlijk		
rij 6	Vogue natuurlijk	Agria natuurlijk		
rij 5	Vogue natuurlijk	Agria natuurlijk		
rij 4	Erwinia Mozart (natuurlijk) (partij 1 hzpc)		Partij 1	
rij 3	Erwinia Mozart (natuurlijk) (partij 1 hzpc)			
rij 2	Erwinia Mozart (natuurlijk) (partij 1 hzpc)			
rij 1	Erwinia Mozart (natuurlijk) (partij 1 hzpc)			

	Spuitspoor				
rij 28					
rij 27					
rij 24	Gezond	Gezond	Gezond		Pootafstand 0.5m
rij 23	Gezond	Erwinia	Erwinia		
rij 22	Gezond	Erwinia	Erwinia		
rij 21	Gezond	Erwinia	Erwinia	Riviera	
rij 20	Gezond	Gezond	Gezond		
rij 19	Gezond	Erwinia	Erwinia		
rij 18	Gezond	Erwinia	Erwinia		
rij 17	Gezond	Erwinia	Erwinia	Kuroda	
rij 16	Gezond	Gezond	Gezond		
rij 15	Gezond	Erwinia	Erwinia		
rij 14	Gezond	Erwinia	Erwinia		
rij 13	Gezond	Erwinia	Erwinia	Kuras	
rij 12	Gezond	Gezond	Gezond		
rij 11	Gezond	Erwinia	Erwinia		
rij 10	Gezond	Erwinia	Erwinia		
rij 9	Gezond	Erwinia	Erwinia	Fontana	
rij 8	Gezond	Gezond	Gezond		
rij 7	Gezond	Erwinia	Erwinia		
rij 6	Gezond	Erwinia	Erwinia		
rij 5	Gezond	Erwinia	Erwinia	Esmee	
rij 4	Gezond	Gezond	Gezond		
rij 3	Gezond	Erwinia	Erwinia		
rij 2	Gezond	Erwinia	Erwinia		
rij 1	Gezond	Erwinia	Erwinia	agria	
	<-- 30 m --> 62 knollen	10m <-- 60m --> 125 knollen	10m <-- 60m --> 125 knollen		

To explore the potential of nature to improve the quality of life

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