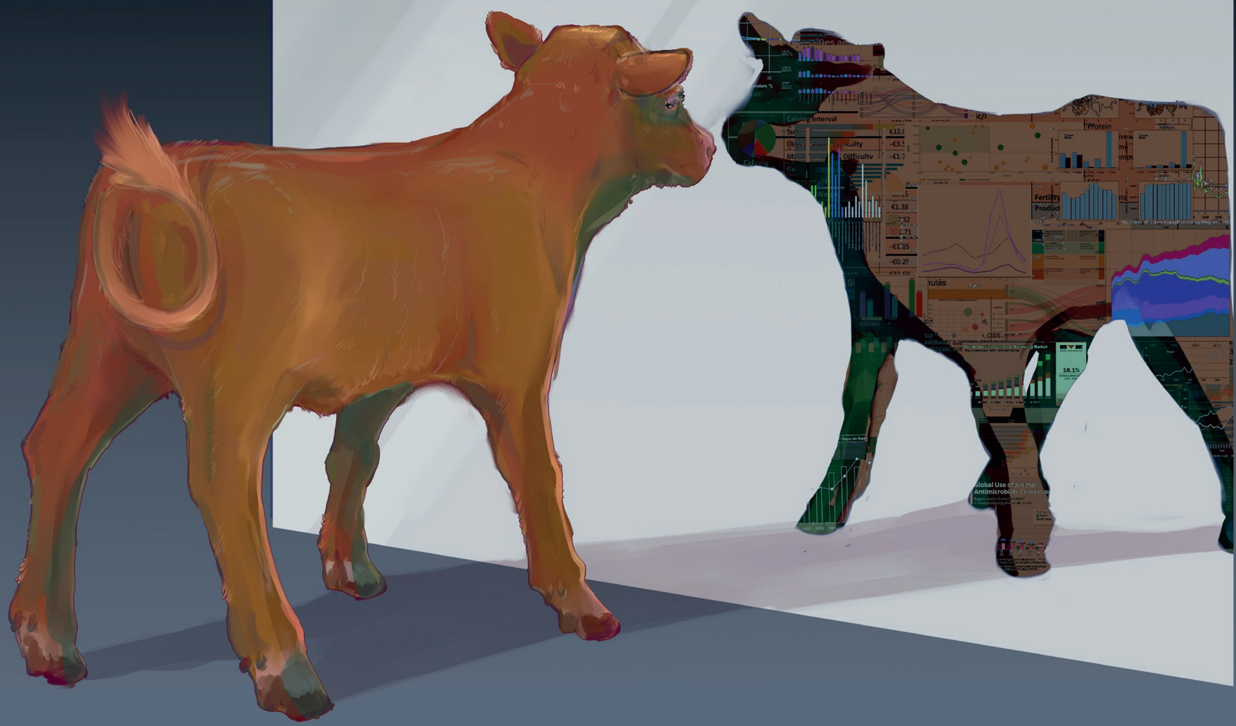
DECODING CALF PATTERNS

Advancing automated health monitoring with algorithmic insights



Dengsheng Sun

Propositions

1. The ‘normal’ activity pattern is abnormal for a calf.
(this thesis)

2. Accuracy of the 3D cameras needs to be improved to further develop Product-Lucrative Farming (also known as PLF).
(this thesis)

3. Experts develop complex systems; visionaries make them simpler.

4. Science-based knowledge helps us understand the dopaminergic system, but it does not help us to control our desires.

5. The disconnect of humans from nature started with our endless strive for convenience in daily life.

6. More female leaders are needed to solve the global crisis caused by male ego.

Propositions belonging to the thesis, entitled

Decoding calf patterns: advancing automated health monitoring with algorithmic insights

Dengsheng Sun

Wageningen, 28 November 2023

Decoding calf patterns

Advancing automated health monitoring with algorithmic insights

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Decoding calf patterns

Advancing automated health monitoring with algorithmic insights

Dengsheng Sun

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Chapter 1 General introduction

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World milk production reached 887 million tonnes in 2020 (FAO, 2022). With such high demand worldwide, dairy cows who produce the milk need to keep giving birth to renew the lactation in order to produce milk. Most female calves will be kept as heifers for the dairy industry, while the male (and some female) calves are not needed. The veal industry was therefore developed (mainly in Europe and North America) to make use of the dairy calves that are not wanted or needed for herd replacement, commonly referred to as 'surplus' calves. Although there are a number of possible routes for surplus dairy calves (Haskell, 2020; Webb *et al.*, 2023), those calves destined for veal production are typically transported from different source dairy farms, sometimes across country borders, at the early age of around two to four weeks to a fattening veal farm (Marcato *et al.*, 2018). At the veal farm, the calves are group-housed, typically in small groups of five to ten, but sometimes in large groups of 40 to 70 calves, with typically 1.8 m^2 per calf, on wooden slatted floors. Veal calves are fed milk replacer in open troughs or buckets if housed in small groups, or via an automated milk feeders if house in large groups, until slaughter for the 'white' veal calves, and for eight weeks for the 'rosé' veal calves. Next to milk replacer, the calves receive solid feed, typically a mixture of concentrates and roughage (e.g. straw) until slaughter at approximately six (white) to eight (rosé) months of age (EFSA AHAW Panel, 2023). Veal calves do not typically receive enrichment, unless housed in the large groups, and do not typically have access to outdoor spaces. This production system allows veal calves to be raised efficiently, allowing each step of the chain to be considered and controlled (Renaud and Pardon, 2022), to end up with relatively high-quality meat products which fetch a high price with consumers, while using minimal resources.

The Dutch veal sector is the biggest veal producer in the EU, accounting for 36% of the total production in 2020 (Berkhout *et al.*, 2021). With around one million veal calves being kept in approximately 1,600 fattening farms[1], the Dutch veal sector produces 1.6 to 1.7 million calves per year (Berkhout *et al.*, 2021). These calves are transported from their source dairy farms all across Europe to the collection centres first, where they are sorted based on weight, breed, or conformation, before being sent to the fattening farms (Damiaans *et al.*, 2019). This dairy-veal chain presents potential concerns for calf welfare, including transportation of young animals, high risk of disease, and barren housing (Webb *et al.*, 2023). One important concern for the farmers in this production system is the high morbidity (Sandelin *et al.*, 2022) and high mortality rates (Bokma *et al.*, 2019; Sandelin *et al.*, 2021), which have a multi-factorial

[1] Source: Landbouw; gewassen, dieren, grondgebruik en arbeid op nationaal niveau (cbs.nl)

etiology: a combination of calf transportation at an early age and hence at an age of immune immaturity (Marcato *et al.*, 2022a), and mixing of animals from many different source farms, hence the exposure to many pathogens (Sandelin *et al.*, 2021).

The result is often a high use of antibiotics at veal farms in the Netherlands (Havelaar *et al.*, 2017), and in many cases, a broad-spectrum antibiotic is used (Jarrige *et al.*, 2017; Bokma *et al.*, 2019). In addition, many antibiotic therapies are applied in group-treatments which makes the veal industry prone to the risk of sub-dosage and consequently an increased risk of development of antimicrobial resistance of pathogens (Jerab *et al.*, 2022), which poses a human health risk, e.g. lower effectiveness of antibiotics treatment in humans. This high levels of antibiotic use and antimicrobial resistance makes the veal industry heavily criticized (EMA/EFSA, 2016), and European society demands veal calves receive better health care, including minimizing morbidity and mortality by limiting transport duration and transporting at an older age, and higher welfare (Dutch Ministry of Agriculture, Nature and Food Quality, 2021; Webb *et al.*, 2023). Animal welfare is defined here as the balance between pleasant and unpleasant experiences throughout an animal's life (FAWC, 2009).

One promising avenue in the improvement of health care in livestock, and specifically in health monitoring, is that of precision livestock farming (**PLF**), which is defined as the continuous and real-time monitoring of animal behaviour, anatomy or physiology, or some environmental variable, to deduce health, welfare, production or reproduction parameters of the animals (Berckmans, 2017). Conventional on-farm health monitoring practice is based on visual appraisal and clinical examinations performed by farmers and veterinarians (McGuirk and Peek, 2014), which is linked to disadvantages such as identifying sick calves late (Timsit *et al.*, 2011; Schroeder *et al.*, 2012) or with medium diagnostic accuracy (Decaris *et al.*, 2022). Many sick calves, hence, remain undetected, which makes it difficult to promptly treat them, leading to greater chances of spread of disease and poorer animal welfare, resulting in a higher use of antibiotics.

Sensor-based data is currently collected on many farms, for example milk yield, composition of dairy cows recorded via milking robots or feed intake of fattening pigs recorded via automated feed dispensers. In veal calves housed in large groups, automated milk feeders record milk feeding behaviour at the individual level. Although these data could say much about the health and welfare of individual animals, the principal use of these types of automated feeding systems is for production efficiency and the application towards improving animal welfare is lagging (e.g. in pigs: Bus *et al.*, 2021). A number of PLF techniques have however been developed in past research, e.g. 3D cameras (Arulmozhi *et al.*, 2021; Wang *et al.*, 2023), accelerometers (Riaboff *et al.*, 2022), for different species, e.g. dairy cows (John *et al.*, 2016; Silva *et al.*, 2021), pigs (Gómez *et al.*, 2021; Tzanidakis *et al.*, 2021), poultry (Li *et al.*, 2020; Olejnik *et al.*, 2022), and to deal with different problems, including health (Niloofar *et al.*, 2021; Džermeikaitė *et al.*, 2023), welfare (Benjamin and Yik, 2019; Rowe *et al.*, 2019; Schillings *et al.*, 2021), and the environmental impact of livestock farming (Tullo *et al.*, 2019; Niloofar *et al.*, 2021). A fully automated health monitoring system for veal calves is, however, still lacking.

The aforementioned general advances in PLF make it possible to start developing an automated tool for health monitoring in veal calves, to assist the conventional way of calf health monitoring. The following developments are crucial for the development and application in practice of PLF tools for health monitoring in veal calves:

1) the decreasing costs and increasing implementation of electronic tools allows for the application of 'sensing solutions' on a large scale, such as in commercial veal fattening farms;

2) behavioural and physiological parameters can nowadays be automatically recorded at individual animal level, continuously and over long periods of time (Caja *et al.*, 2016), allowing to follow the course of the whole (or as long as possible) fattening period;

3) previous studies reported automated detection of specific diseases such as respiratory disease (Puig *et al.*, 2022; Garrido *et al.*, 2023), which proved the feasibility of this PLF approach.

We expect a large amount of work in PLF will go towards organising and analysing the various datasets, and that the development of new PLF systems will require a number of careful steps. One of the early required steps is the study and understanding of healthy, normal patterns of calf behaviour, anatomy or physiology, prior to attempting to identify 'abnormalities' and 'deviations' which might point to some sort of problem, e.g. health or welfare issues. This step includes the investigation of individual variation and more or less constant traits (e.g. personality) that consistently affect these patterns. Another critical step is the testing and comparison of various, available models to describe and predict these patterns, with a particular interest in (deep) supervised machine learning techniques (Mahmud *et al.*, 2021; Oliveira *et al.*, 2021).

The advantage of machine learning in this context is that these systems can learn and adapt according to the data, without the need for human input, to develop the most adequate algorithms to describe and predict patterns of data. The terms ‘supervised’ indicates that the system receives a so-called ‘training’ dataset, whereby manual, direct, human-based outcomes are included for teaching. ‘Deep’ learning refers to a type of machine learning which involves multiple layers in the network to progressively extract more and more higher-level information.

In the context of PLF applied to veal growth and health monitoring, various types of (deep) supervised machine learning are of interest, e.g. linear regression (**LR**); support vector regression (**SVR**); random forest (**RF**); extreme gradient boosting (**XGB**); and a convolutional neural network (**CNN**). These methods are used for classification to model either linear or non-linear relationships. LR is the simplest method and involves a linearly weighted sum of the features of the data (Hastie *et al.*, 2017), and is often used as a benchmark to compare with other machine learning methods (Dohmen *et al.*, 2021). This approach, however, has the restriction that it may be insufficient to model behaviour that deviates from a linear relationship. SVR overcomes this problem and models non-linearities (Drucker *et al.*, 1996). Another supervised machine learning method which can be used for classification as well as regression is the RF (Hastie *et al.*, 2017). It uses ensemble learning and it combines predictions from multiple decision trees to obtain a more accurate prediction than an individual tree. RF is trained by iteratively building decision trees based on randomly selected data points and predicts a value on a new data point by averaging across the predicted values over all the trees. RF can model non-linearities but has a drawback in that it needs to be trained with expected values thus it may be inaccurate while predicting previously unseen ranges of values. XGB uses gradient boosting on the decision tree algorithm for regression or classification (Chen and Guestrin, 2015). In this approach, new models are created that predict the residuals or errors of existing models and are then added together to contribute to the final prediction. CNN for regression consists of a deep neural network without a final non-linear layer, which is typically used for classification (Goodfellow *et al.*, 2016).

Scientific challenges need to be noted, however, with the advances of PLF in veal calf industry. Firstly, a holistic view is necessary in terms of what are the available PLF techniques and which techniques are promising for health monitoring in veal calves. Secondly, before identifying a sick calf, we need to learn what a healthy calf look like with the available PLF tools, e.g. using accelerometers to record activity patterns in healthy calves.

Thirdly, with the current advances of PLF, what are the promising variables worth looking into for monitoring calf health and growth, in addition to the conventional health-monitoring variables? The aim of this thesis was to lay the foundations for the development of an automated health monitoring system for veal calves by developing algorithms that help describe and predict calf patterns of behaviour and anatomy. Three paths were followed to achieve this aim:

1. First, a systematic review of past research into PLF techniques to monitor health in calves was conducted, to acquire an overview of current knowledge (including methods and tools), and gaps between current status and a desired situation (**Chapter 2**). In particular, we constructed a four-step framework that should be followed carefully for automated health monitoring in calves.
2. Second, behavioural patterns, in this case those linked to activity, were modelled and scrutinised to describe healthy, normal patterns of behaviour in calves throughout the fattening period (**Chapter 3**). Generalised additive models is reported to be promising in fitting nonlinear relationships, while minimizing instances of overfitting by optimizing a maximum likelihood estimation (Perttu *et al.*, 2023).
3. Third, four different (deep) supervised machine learning algorithms and a CNN regressor were tested and compared in their performance in the prediction of body weight (**BW**) based on 3D images (**Chapter 4**). BW is a robust indicator of growth performance and health for cattle (Segerkvist *et al.*, 2020). A regular body weight measurement could support the identification of deviations from an estimated growth curve, allowing for timely adjustments in feeding and assistance in health monitoring. We explored the use of computer vision and appropriate machine learning models: LR, SVR, RF, XGB, and a CNN.

In **Chapter 5**, I summarized and discussed the results of all chapters in an integrated way and identify the potential applications of current results, how the results can contribute to alleviate the problem of high antibiotic use and subsequently improve calf welfare and health. I also briefly shared the further plans of the project in which my thesis is embedded.

This thesis focuses on learning about the patterns in healthy calves, which lay the foundation for the next step of detecting ‘deviations’ of patterns in individual calves. Furthermore, along this research approach, the author noticed certain risks linked to the development of PLF-based solutions. In chapter five, I challenge the logic behind this approach, point out the missing values in the process of developing and deploying these PLF tools, and invite readers to think about alternatives on how we could reduce the antibiotic use in veal rearing, with a more animal-oriented approach, to answer the societal demand such as farmers' need, the nitrogen crisis in the Netherlands, to address global crises including global warming and the global resource depletion, and more importantly, to let PLF be a tool, not the goal.


stage2
stage3

Chapter 2 A systematic review of automatic health monitoring in calves: glimpsing the future from current practice

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Abstract

Infectious diseases particularly bovine respiratory disease (**BRD**) and neonatal calf diarrhoea (**NCD**) are prevalent in calves. Efficient health monitoring tools to identify such diseases on time are lacking. Common practice (i.e. health checks) often identifies sick calves at a late stage of disease or not at all. Sensor technology enables the automatic and continuous monitoring of calf physiology or behaviour, potentially offering timely and precise detection of sick calves. A systematic overview of automated disease detection in calves is still lacking. The objectives of this literature review were hence: 1) to investigate previously applied sensor validation methods used in the context of calf health, 2) to identify sensors used on calves, the parameters these sensors monitor, and the statistical tools applied to identify diseases, 3) to explore potential research gaps and to point to future research opportunities. To achieve these objectives, systematic literature searches were conducted. We defined four stages in the development of health monitoring systems: 1) sensor technique, 2) data interpretation, 3) information integration, and 4) decision support. Fifty-five articles were included (stage one: 27, stage two: 19, stage three: 9, and stage four: 0). Common parameters that assess the performance of these systems are sensitivity, specificity, accuracy, precision, and negative predictive value. Gold standards that typically assess these parameters include manual measurement and manual health assessment protocols. At stage one, automatic feeding stations, accelerometers, infrared thermography cameras, microphones, and 3D cameras are accurate in screening behaviour and physiology in calves. At stage two, changes in feeding behaviours, lying, activity, or body temperature corresponded to changes in health status, and point to health issues earlier than manual health checks. At stage three, accelerometers, thermometers, and automatic feeding stations have been integrated into one system which was shown to be able to successfully detect diseases in calves, including BRD and NCD. We discuss these findings, look into potentials at stage four and touch upon the topic of resilience, whereby health monitoring system might be used to detect low resilience (i.e. prone to disease but clinically healthy calves), promoting further improvements in calf health and welfare.

Keywords: health monitoring, calf, early disease detection, precision livestock farming, sensor

2.1 Introduction

Within the dairy and veal production systems, diseases such as bovine respiratory disease (**BRD**) and neonatal calf diarrhoea (**NCD**) are highly prevalent in young calves (Cramer *et al.*, 2016). Despite slightly different prevalence rates (Sutherland *et al.*, 2018), disease types affecting dairy and veal calves are similar (McGuirk and Peek, 2014; Marcato *et al.*, 2018; Lowe *et al.*, 2019b). BRD symptoms include hampered respiration, nasal discharge, and coughing (Brscic *et al.*, 2012). A direct symptom of NCD is extremely watery faeces (Cramer *et al.*, 2016). Potential risk factors for BRD include: poor immune system development and function (typically found in calves provided with a low body weight (Brscic *et al.*, 2012), or provided with poor quality or inadequate amounts of colostrum, Edwards, 2010), indoor housing, trough feeding of milk replacer in the early stages of fattening (Brscic *et al.*, 2012), and management practices such as weaning, comingling, and castration (Smith and Step, 2020). Potential risk factors for NCD include high exposure to pathogens causing NCD, factors related to host resistance or susceptibility to disease, e.g. low quality and quantity of colostrum, and factors about the environment that favour the host or agent, e.g. high stocking density, too high or too low ambient temperature and air humidity (Smith, 2012).

Diseases in calves cause significant economic losses (Yazdanbakhsh *et al.*, 2017; Wang *et al.*, 2018), due to treatment (Schaefer *et al.*, 2012), impaired growth and mortality (Windeyer *et al.*, 2017), and impaired calf welfare (Millman, 2007). Moreover, antibiotic resistance, a major concern in human and veterinary medicine (Awasthi *et al.*, 2016), is a serious problem in the veal industry (Havelaar *et al*., 2017; Mitrenga *et al.*, 2020). In addition, the overuse of antibiotics might result in the contamination of surface water near farms due to residues in the urine and faeces of animals (Mostert, 2018). Given the all-encompassing impact of calf health on sustainability aspects, it is essential that we develop accurate, timely, and practical systems to identify sick calves, both in the dairy and veal sectors.

The common practice for identifying diseases in calves is based on visual appraisal and clinical examinations performed by farmers and veterinarians (McGuirk and Peek, 2014). This practice is linked to a number of disadvantages: 1) calves identified as sick already show clear clinical symptoms and may have already been sick for a while. For example, clinical signs of BRD are only visible 12 to 36 hours after the onset of fever (Timsit *et al.*, 2011) and clinical signs of NCD are visible when much of the associated tissue damage to the intestinal submucosa has already occurred (Schroeder *et al.*, 2012). 2) Visual appraisal and clinical examinations are typically poor at identifying sick calves. For example, in a study diagnosing BRD in beef calves using clinical examination, the estimated sensitivity and specificity were 61.8% and 62.8%, respectively (White *et al.*, 2009). Many sick calves, hence, go undetected, which makes it difficult to promptly treat them, leading to greater chances of spread of disease, poorer animal welfare, and greater negative impacts on economy and environment, overall leading to poor sustainability of production systems involving calves.

Improved methods to detect health problems accurately and on a timely basis in individual calves are warranted. The decreasing cost and increasing implementation of electronic tools allows for the application of 'sensing solutions' to animal farming. Behavioural and physiological parameters can nowadays be automatically recorded at individual animal level, continuously and over long periods of time (Caja *et al.*, 2016). During the past decade various sensor data models have been proposed for automatic health monitoring systems in dairy and veal calves. To date, however, there has been no literature review presenting the associated gaps in research, while this has previously been done for pigs (Matthews *et al.*, 2016; Martinez-Aviles *et al.*, 2017) and dairy cows (Rutten *et al.*, 2013). The objectives of this literature review were hence: 1) to investigate previously applied sensor validation methods and gold standards, 2) to identify how sensors are used and validated in calves, 3) to explore potential research gaps to point to opportunities for future research.

2.2 Methods

2.2.1 Definitions

Animals included in this review were bovine animals aged less than one year, these include 'calf' or 'calves' (pre-weaned or weaned), heifers (weaning to one year of age), growing bulls (after arrival at the fattening farm up to one year of age), beef cattle (early fattening period till one year of age). Precision livestock farming (**PLF**) is defined based on Berckmans (2008) as 'measuring variables on the animals, modelling these data to select information, and then using these models in real time for monitoring and control purposes'. We defined the following terms - SENSOR: an automatic tool capable of recording activities, behaviours, physiology, and morphology of calves continuously; MODEL: a mathematical tool that describes the relations between the sensor output and the actual values of the measured parameters of the physical environment; VALIDATION: the process of determining the measurement ability of automatic tools relative to a gold standard using statistics.

We defined four stages of development of a particular sensor technique for disease detection based on Rutten *et al.* (2013) (Fig.1) - *stage one*: SENSOR TECHNIQUE - applying sensor technology to record behavioural or physiological parameters in animals, visualizing these parameters, *stage two*: SENSOR INTERPRETATION - changes in data are detected and connected to changes in behaviour and physiology with an established link to the animal's health status; *stage three*: INFORMATION INTEGRATION - multiple data resources, e.g. treatment records and sensor data, are integrated to direct the farmer to potential problems that need attention; stage four: DECISION SUPPORT – a sensor system that aids to make a decision, e.g. whether to treat an animal or not; what to treat the animal for?

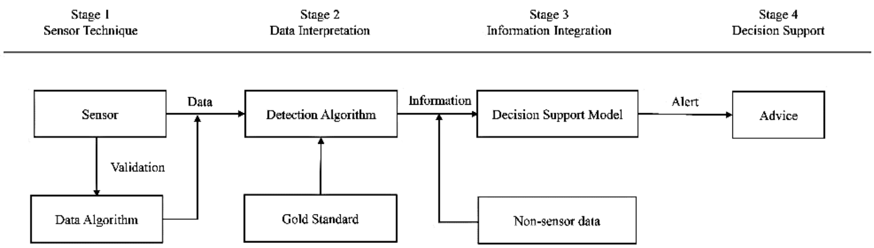


Fig. 1 Development stages

2.2.2 Inclusion and Exclusion Criteria

Peer-reviewed scientific articles applying sensors to calves were eligible for inclusion. Only articles based upon original data were included. Included articles were written in English, with complete, full-text documents available. To provide up-to-date review, only articles published between 2009 and 2021 were included. Manuscripts published after the completion of the literature search were not included (i.e. after May 10, 2021). Exclusion and inclusion criteria for the systematic review were based on an previous work by Beaver *et al.* (2019) and agreed upon by all co-authors.

2.2.3 Search Strategy

Systematic searches were conducted using the Web of Science Core Collection database because it has high coverage rates of animal behaviour and welfare and bio-system engineering journals with significant PLF contents.

The following search terms were applied: (calf OR calves OR dairy calf OR dairy heifer OR heifer calf OR heifers OR young cattle) AND (BRD OR bovine respiratory disease OR calf comfort OR calf health OR diarrhea OR group housing OR health OR precision livestock OR precision livestock farming OR proneness to disease OR welfare) AND (automatic OR automated measurement OR automated measures OR detection OR diagnosis OR disease monitoring OR evaluation OR modeling OR non-invasive detection OR prediction OR validation) AND (accelerometer OR activity sensor OR artificial intelligence OR automatic milk feeder OR bioacoustics OR computer vision OR electronic monitoring OR infrared thermography OR low-cost sensor OR non-invasive technology OR radio frequency identification OR reticulo-rumen bolus OR statistical process control OR sound analysis OR 3D sensor). The selection of these search terms was based on initial screening of relevant articles to gain general background information and expert opinion.

2.2.4 Selection Process

The primary outcomes were selected based upon a four-step screening and appraisal process (Fig. 2):

Step one. Scanning the titles - filter out irrelevant results such as review articles in automatic detection, original articles of health monitoring in calves without applying sensor technology, or original articles of automatic health monitoring systems in mature cattle or other species.

Step two. Evaluating abstracts - identify and remove irrelevant articles.

Step three. Snowballing - checking and selecting references within selected articles.

Step four. Eligibility. Full texts of the remaining articles were read in detail. Original experimental studies were excluded if not aiming at health monitoring in calves up to one year of age using sensor technology.

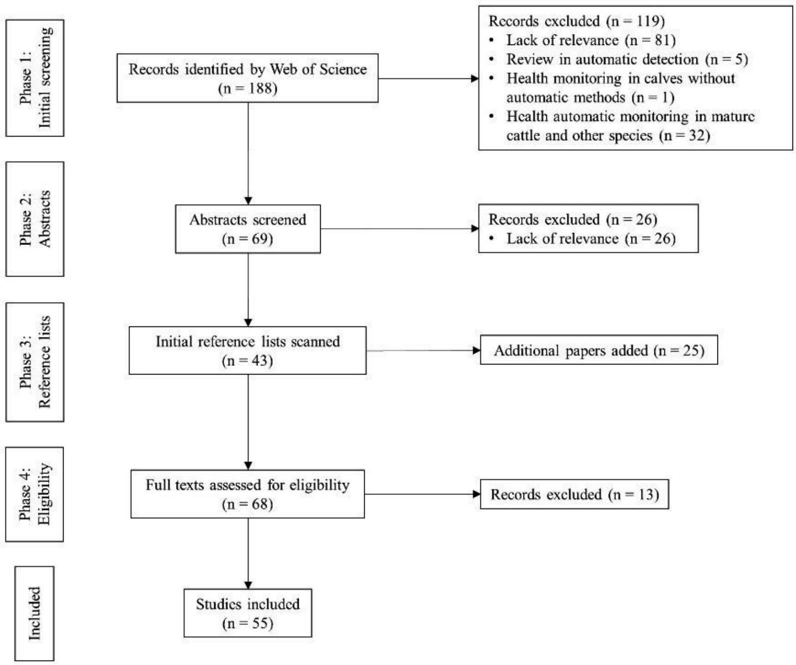


Fig. 2 Article selection process

2.2.5 Data Extraction

From each included article, where applicable, we recorded the objectives, animal category, parameters measured, sample size, gold standards for validation, sensors used, measurements used to assess the performance of the sensors or algorithms. Missing information were noted down as ‘not available’. The results were pooled in the form of Tables (Appendix 1). The reliability for data extraction was tested by author 1 (DS) on a random subset of 20 articles, with a result of 100% agreement.

2.2.6 Data Management

Extracted data were entered into and managed in excel spreadsheets (version 2016, Microsoft Corp., Redmond, WA, RRID:SCR_016137).

2.3 Results and Discussion

Following the article selection process described above, 55 articles were included in this review (Fig. 2). As shown in Fig. 3, 27 articles fell into *stage one* (sensor technique), 19 articles fell into *stage two* (data interpretation), and 9 articles fell into *stage three* (information integration). We found no articles at *stage four* (decision support).

Studies at these different stages use different validation methods and gold standards. Studies at stage one aim to check that a given sensor is accurately recording a particular behavioural or physiological parameter of interest. These studies typically use (a) manually collected parameter(s) as gold standard for their validation, for example, video observations of lying bouts or rectal body temperature measurements using a thermometer. Stage two and stage three studies aim to identify sick calves as early as possible. Stage two and three studies develop and test algorithms applied to sensor data to accurately detect sick individuals. Manual health assessment protocols are typically used as gold standards to develop and test these algorithms (Table 1).

We first define what is meant by 'validation' in this review as well as define the terms used in this context, i.e. sensitivity, specificity, accuracy, and positive and negative predictive value. We follow up with a description of the different gold standards that have been used at the different stages of investigation. Next, we describe the various sensors that have been used in calf health monitoring research, the parameters these sensors record, and their accuracies in these recordings. We end by presenting the current research at stage two (data interpretation) and stage three (information integration), revealing important knowledge gaps between stage three and stage four (decision support), suggesting the direction for future study of which will enable the bridging of these gaps, hence reaching automated health-related data interpretation and complete decision support systems for calf production systems.

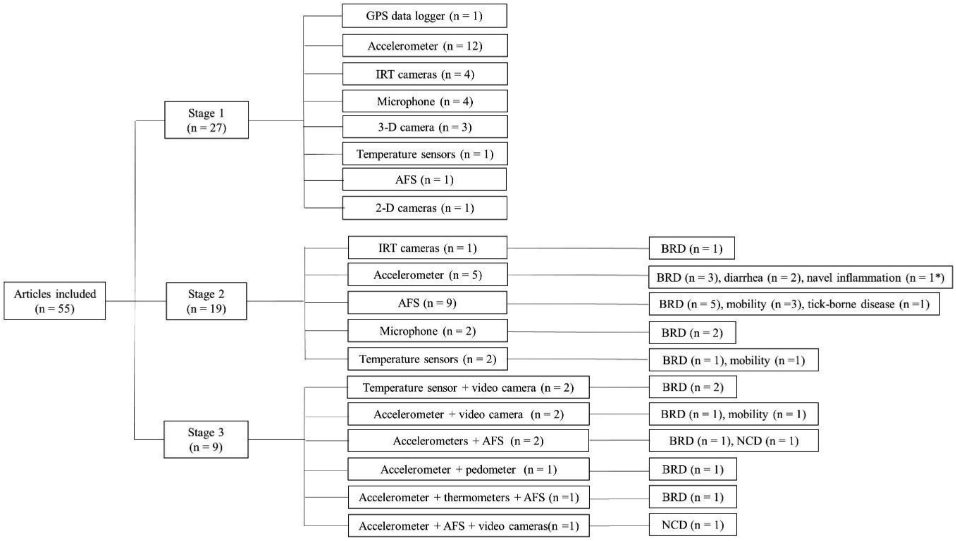


Fig. 3 Distribution of stages of included articles.

* in Studds *et al.* (2018) both diarrhoea and navel inflammation were studied.

2.3.1 Validation

The validation assessments at different stages of studies share common principles. Validation assessments are typically calculated via so-called confusion matrices (Table 2) (Leary, 2020).

Table 2* Confusion matrix

Predicted / Actual	Positive	Negative
Positive	True positive	False negative
Negative	False negative	True positive

* Table 2 is presented here for better explaining the text.

Confusion matrices reveal relationships between the sensor of interest, the selected gold standard (see below formulas for: sensitivity, specificity, accuracy, precision, and negative predictive values) and the underlying prevalence of the disease interest. 'Positive and negative' show the sensor (or model) output (a response of 'yes' or 'no' to the disease detection), while 'true and false' reflects whether the sensor (or model) output is in line with the gold standards in a pre-specified time window (i.e. whether the prediction matches the reality). When comparing article outcomes it should be noted that sensitivity and specificity are affected by characteristics of the sensor, while accuracy, precision and negative predictive values are affected by the prevalence of disease or behaviour based on the dataset; the higher the prevalence, the better the accuracy, precision and predictive values for the given dataset. Model developments are usually aimed to enhance the contrast in a sensor system output for the purpose of threshold evaluations (e.g. sensitivity, specificity, or accuracy) over a given range. Common methods used for model developments are correlation, area under curve (Leary, 2020), and receiver operating characteristic curves (Leary, 2020).

$$Sensitivity = \frac{true\ positives}{(true\ positives + false\ negatives)}$$

$$Specificity\ = \frac{true\ negatives}{(false\ positives\ +\ true\ negatives)}$$

$$Accuracy = \frac{(true\ positives\ +\ true\ negatives)}{(true\ positives\ +\ true\ negatives\ +\ false\ positives\ +\ false\ negatives)}$$

$$Precision\ (positive\ predictive\ value) = \frac{true\ positives}{(true\ positives\ +\ false\ positives)}$$

$$Negative\ predictive\ value\ = \frac{true\ negative}{(true\ negative\ +\ false\ negative)}$$

2.3.2 Gold Standard

To obtain a sound validation of a sensor or PLF system, an objective ‘gold standard’ is needed. In this regard, studies at stage one to stage four require different gold standards. At stage one, gold standard means ‘variables of interest’, i.e. behavioural or physiological parameters; at stage two, three, and four, gold standard usually refers to the identification of disease, typically via a manual ‘clinical examination’.

Stage one studies, where sensors are checked directly for their ability to record behavioural or physiological parameters, tend to use manual sampling of these behavioural or physiological parameters. For sensors recording behavioural parameters, behavioural observations of videos, continuous or at regular intervals, is a commonly used reference for validation. Continuous sampling of focal animals will provide the most accurate data for calf behaviour, but is a time consuming exercise. For certain, long-term, so called ‘state’ behaviours, instantaneous scan sampling at regular intervals may provide an accurate enough gold standard and is less time consuming. For example, meal time and frequency over a 3-day period can be detected accurately with instantaneous scan sampling at short intervals of 30 seconds and one minute (Miller-Cushon *et al.*, 2011). Disadvantages associated with video observations include difficulty in recognizing individuals from the videos (Robert *et al.*, 2011) and observer error (Kour *et al.*, 2018), as well as problems with obstacles obstructing the behaviour of interest (e.g. head of calf behind bucket) or the quality of the video being too poor to identify with absolute certainty subtle behaviours (e.g. tongue rolling inside the mouth) (personal observation of the authors).

For sensors recording physiological parameters, manual measurements of these physiological parameters are also used as gold standards. Sensors recording body temperature, e.g. body surface temperature (Nogami *et al.*, 2013), eye temperature (Scoley *et al.*, 2019; Bell *et al.*, 2020), and rectal area temperature (Scoley *et al.*, 2019), typically use manually recorded rectal temperature as gold standard. When validating body dimensions in calves and heifers, manual measurements of body weight and dimensions are common, including body weight (Song *et al.*, 2014; Nir *et al.*, 2018; Pezzuolo *et al.*, 2018), hip height (Song *et al.*, 2014; Nir *et al.*, 2018), and wither height (Nir *et al.*, 2018).

With increasing research into validating sensors in terms of how accurately they record behaviour or physiological parameters, previously validated sensors may be used as automated gold standard to validate new sensors, which significantly reduces labour required for these types of stage one studies. The Hobo Pedant G Data logger, for example, has been previously used as a gold standard to validate another accelerometer, the AfiTag II for lying behaviour and step count (Swartz *et al.*, 2016).

Stage two and three studies aim to identify sick calves. Here, a clinical examination is the most commonly used gold standard for disease diagnosis (Table 1) (Borderas *et al.*, 2009; Voss *et al.*, 2016; Swartz *et al.*, 2017; Hixson *et al.*, 2018; Shane *et al.*, 2018; Toaff-Rosenstein *et al.*, 2018). Various protocols have been used in this type of study, such as the Wisconsin clinical respiratory score (Vandermeulen *et al.*, 2016) and the Wisconsin calf health scoring chart (Johnston *et al.*, 2016). Further information can be added to these clinical examinations to compliment the gold standard, including metadata like management information (e.g. calf registration or enrolment data), morbidity and mortality data from the farm (Knauer *et al.*, 2017; Knauer *et al.*, 2018), BW (Jackson *et al.*, 2016; Studds *et al.*, 2018; Kayser *et al.*, 2019), post-mortem examination (Moya *et al.*, 2015; Toaff-Rosenstein *et al.*, 2016), or blood parameters (Hanzlicek *et al.*, 2010; Timsit *et al.*, 2011; Schaefer *et al.*, 2012; Wolfger *et al.*, 2015a; Johnston *et al.*, 2016; Vandermeulen *et al.*, 2016; Knauer *et al.*, 2017;

Oliveira *et al.*, 2018b). Of all the clinical examination protocols, the (modified) Wisconsin calf health score chart was the most commonly used protocol (Johnston *et al.*, 2016; Swartz *et al.*, 2017; Hixson *et al.*, 2018; Swartz *et al.*, 2020; Duthie *et al.*, 2021). Gold standards without clinical examination, for example, from blood analysis (Carpentier *et al.*, 2018), or a combination of BW, biochemical parameters from blood and faecal samples, and rectal temperature (Szyszka *et al.*, 2012) have also previously been used. Clinical examination can be combined with clinical chemistry, for example, via blood sampling, to improve the accuracy of health assessment.

Visual appraisal of disease has been found to have low specificity and be highly variable between observers based on their level of experience (Amrine *et al.*, 2013). Thus errors from the clinical examinations may transfer to the corresponding models (Moya *et al.*, 2015). Though invasive, the addition of data from clinical chemistry is likely to improve the development of algorithms (Wolfger *et al.*, 2015a), while also adding information about specific pathogens to the gold standard (Sutherland *et al.*, 2018). It must however be noted that including clinical chemistry parameters into a gold standard, may lead to 'intermediate values' (i.e. neither true positive nor true negative), because these animals may be either successfully resisting or slowly succumbing to diseases (Schaefer *et al.*, 2012).

When performing time consuming clinical examinations for use as a gold standard, the frequency of these examinations needs to be carefully considered. Daily clinical examinations of calves can provide better timely reference, at the cost of disturbance to the group and high labour requirements. While too low frequency of clinical examinations will result in late detection, hence makes algorithm development for early onset of disease more difficult (Hogeveen *et al.*, 2010). Previous research applied different frequencies - for clinical examinations, ranging from daily to weekly (Table 1). Clinical examinations combining two different frequencies applied at different life stages were also found, for example before (twice a week) and after the weaning period (once per week) of dairy calves (Johnston *et al.*, 2016; Vandermeulen *et al.*, 2016). To the authors knowledge, no study has yet compared the effect of different frequencies of clinical examinations on the accuracy of disease detection models.

Improvements are necessary for the clinical examinations used as gold standards for the development of algorithms to detect diseases in calves. Firstly, training in clinical examination and high inter-observer consistency are required. Secondly, to better relate clinical examinations to model outcome, more specific research questions need to be raised, including the specific health, productivity and welfare concerns linked to calves of different ages (Finney *et al.*, 2018).

In summary, clinical examination is the most common gold standards used in the development of algorithms to identify sick calves. The Wisconsin calf health score chart was identified as a commonly used protocol for clinical examination in this context. This method, however, does not seem accurate enough, with a sensitivity of 62.4%, and specificity of 74.1% (Buczinski *et al.*, 2015). Therefore, clinical references with high accuracy, with consistent guidelines, and easy-to-follow protocols are needed for disease detection in calves. A standardized clinical scoring system will benefit the validation of the sensors and algorithms, making it easier to compare the performance of different algorithms.

2.3.3 Stage one: Sensor Technology Used in Calves

Data sources used in calves include automatic feeding stations (**AFS**), accelerometers, microphones, infrared thermography (**IRT**) cameras, temperature sensors (i.e. boluses, thermometers), radiofrequency identification (**RFID**) chips, 3D cameras, 2D cameras.

2.3.3.1 Automatic Feeding Stations

AFS, such as automated milk feeders for pre-weaned calves and automatic concentrate bunks for post-weaned calves and water bins, have been used often in studies aimed at automated health monitoring in young calves, hence stage two research. These AFS can measure a wide range of parameters linked to feeding and drinking patterns, including daily feed intake, frequency and duration of rewarded and unrewarded visits, drinking speed (milk), water drinking behaviour (intake, time, and frequency), and other feeding behaviours (head-down duration at the AFS, time-to-bunk: time to approach feeding stations following feed-truck delivery, and duration of unrewarded visit intervals). AFS seem to be able to measure feeding time, water drinking time, feed intake per visits, water intake per visits with high correlation compared to the gold standards (r^2 =0.917, 0.963, 0.973 and 0.986, respectively) (Oliveira *et al.*, 2018a).

2.3.3.2 Accelerometers

Accelerometers are attached to the body of the calf, generally to one of the limbs, neck, or ear(tag). They measure accelerations and are typically used to assess various activity related behaviours. Accelerometers are accurate in recording calf behaviours, including lying time

(Trénel *et al.*, 2009; Bonk *et al.*, 2013; Swartz *et al.*, 2016; Finney *et al.*, 2018; Roland *et al.*, 2018), lying bouts (Trénel *et al.*, 2009; Bonk *et al.*, 2013; Swartz *et al.*, 2016; Roland *et al.*, 2018), standing time (Trénel *et al.*, 2009; Roland *et al.*, 2018), standing bouts (Trénel *et al.*, 2009), step counts (de Passillé *et al.*, 2010; Swartz *et al.*, 2016), locomotion time (Roland *et al.*, 2018), and gait scoring (de Passillé *et al.*, 2010), feeding time (Wolfger *et al.*, 2015b; Roland *et al.*, 2018), sucking behaviour from dams (Kour *et al.*, 2018), and licking or sucking at objects, other calves' bodies, or own body (Roland *et al.*, 2018). After more than 10 years of development, accelerometers are now used to record a broader variety of behaviours and more detailed behavioural patterns, for example, recognizing between galloping, trotting, and walking (de Passillé *et al.*, 2010), and recording behaviours such as eating, water drinking, chewing, positive social interactions, self-grooming, and inactivity (Rodriguez-baena *et al.*, 2020). Step counts were originally measured by pedometers recoding steps taken in a certain period of time (Hanzlicek *et al.*, 2010). This activity parameter was later integrated into accelerometers (de Passillé *et al.*, 2010; Szyszka *et al.*, 2012; Pillen *et al.*, 2016; Swartz *et al.*, 2016; Swartz *et al.*, 2017).

2.3.3.3 Temperature Sensors

Boluses, IRT cameras, and thermometers are used to measure body temperature. These temperature sensors have been developed to record body temperature at different anatomical areas, enabling the measurement of rectal temperature (Toaff-Rosenstein *et al.*, 2016; Toaff-Rosenstein *et al.*, 2018) or temperature around the rectal area (Scoley *et al.*, 2019), reticulo-rumen temperature (Timsit *et al.*, 2011; Voss *et al.*, 2016), eye temperature (Schaefer *et al.*, 2012; Lowe *et al.*, 2019b; Scoley *et al.*, 2019; Bell *et al.*, 2020; Lowe *et al.*, 2020), cheek temperature (Lowe *et al.*, 2019b; Lowe *et al.*, 2020), back, shoulder, and side temperature (Lowe *et al.*, 2019b), and temperature at the base of the tail (Nogami *et al.*, 2013). These cameras have also shown high accuracy in measuring cheek temperatures (Lowe *et al.*, 2020), but do not found to be highly accurate in measuring temperature around the rectal area (Scoley *et al.*, 2019) or core body temperature (Bell *et al.*, 2020). In terms of eye temperature, IRT cameras seem to show varying levels of correlation between eye temperature and rectal temperature, e.g. high correlation ($R^2 \geq 0.99$) (Lowe *et al.*, 2020), low correlation ($R^2 \leq 0.32$) (Scoley *et al.*, 2019). A prototype thermometer provided by Nogami *et al.* (2013) has been found to measure tail temperature with high correlation compared to rectal temperature in calves.

2.3.3.4 Other Sensors and Techniques

Microphones, when integrated into sound acquisition systems, can detect abnormal cough sounds (Ferrari *et al.*, 2010; Vandermeulen *et al.*, 2016; Carpentier *et al.*, 2018) and rumination sounds in calves (Burfeind *et al.*, 2011; Lopreiato *et al.*, 2018; Rodrigues *et al.*, 2019). The performance of microphones varied in calves of different ages. Microphones accurately recorded rumination time in heifers older than 11 month old (Burfeind *et al.*, 2011) and in pre-weaned calves (Lopreiato *et al.*, 2018), but overestimated rumination time in weaning calves (Rodrigues *et al.*, 2019). RFID ear tags can be applied to monitor grooming behaviour (measured via proximity to a brush) in heifers (Toaff-rosenstein *et al.*, 2017). IRT cameras have also been used to assess respiration rate in calves, at a high level of accuracy (Lowe *et al.*, 2019a).

With the application of approaches such as computer vision or machine learning, an even broader range of parameters might be recorded with the available sensors. For example, Carslake *et al.* (2021) applied machine learning approaches to multi-class behaviour identification (including locomotor play, self-grooming, ruminating, non-nutritive suckling, nutritive suckling, active lying, and non-active lying) as well as behaviour quantification (i.e. behaviour distribution) using a single sensor (comprised of an accelerometer and gyroscope) in calves. Computer vision allowed 2D cameras to identify multiple behaviours, for example, pen entering, pen leaving, standing or lying static behaviour, turning, feeding and drinking behaviours (Guo *et al.*, 2020). 3D cameras can monitor growth and morphology (i.e. BW, body mass, hip height, and withers height) in young calves and heifers (Song *et al.*, 2014; Nir *et al.*, 2018; Pezzuolo *et al.*, 2018).

Knowing which parameters sensors (or sensor combinations) can accurately measure can contribute to the development of an efficient sensor system at stage two and three. For example, accelerometers are not accurate in screening rumination time in calves (Wolfger *et al.*, 2015b), but this can instead be achieved by microphones (Burfeind *et al.*, 2011; Lopreiato *et al.*, 2018). Both accelerometers and AFS can record feeding and water drinking behaviours, but AFS can record these behaviours directly without having to apply statistical models and are non-intrusive, i.e. not attached to the animal (Rodriguez-baena *et al.*, 2020).

To sum up, available sensors (AFS, accelerometers, IRT cameras, microphones, and 3D cameras) are accurate in measuring different behavioural or physiological parameters in calves, and approaches such as machine learning and computer vision broaden the range of behaviours sensors can record. Future work should further develop behaviour classification and quantification by applying computer vision and machine learning approaches.

2.3.4 Stage two: Data Interpretation - Outcomes of Algorithms

In order to develop a sensor-based system that detects sick calves, i.e. sensor technology combined with algorithms, stage two studies must follow three steps: 1) identify how behavioural or physiological parameters change with disease, identified via a gold standard (this includes the selection of both parameters of interest and corresponding sensors), 2) investigating how these behavioural and physiological changes vary at which stage of disease they can first be detected; and 3) developing and testing the accuracy (or performance) of algorithms in detecting sick calves based on changes in these behavioural and physiological parameters. In this section, we highlight the algorithms that can detect diseases prior to clinical confirmation (Table 3), and summarize: 1) changes in behavioural and physiological parameters in response to disease, and 2) time course - disease states in animals typically lead to both behavioural and physiological changes over time.

2.3.4.1 Changes in Feeding Behaviours

Feeding behaviours and patterns, including intake, frequency, speed and duration at various time ranges, are commonly used parameters for the early detection of disease in calves (Johnson *et al.*, 2002; Svensson *et al.*, 2007). Note that most studies look at feeding behaviours aggregated at a daily level. With the application of RFID, individual calves are identified at AFS, whereby individual feeding behaviours can be recorded. For example, pre-weaned calves diagnosed with BRD drank less milk on the day of clinical examination (Swartz *et al.*, 2017) and on the first day of treatment (Knauer *et al.*, 2017), drank milk slower four days prior to the clinical examination (Knauer *et al.*, 2017), and performed less unrewarded visits to the milk dispenser three days prior to (Johnston *et al.*, 2016), and on the first day of treatment (Knauer *et al.*, 2017). Moreover, net daily energy intake (calculated for each calf by summing daily milk replacer and concentrate intake values) (Johnston *et al.*, 2016) and DMI (Jackson *et al.*, 2016), were reduced in BRD-infected calves prior to the clinical examination, e.g. three days in Johnston *et al.* (2016); 6.8 days in Jackson *et al.* (2016). In calves diagnosed with NCD, daily milk intake and time at water trough dropped four days prior to clinical examination (Lowe *et al.*, 2019b).

2.3.4.2 Changes in Activity

Changes in activity parameters, such as step counts and lying behaviours, are used to detect sick calves. In calves diagnosed with BRD, for example, step counts (<6 days), lying bouts (<5 days), standing time (<1 day) were reduced (Pillen *et al.*, 2016). In calves diagnosed with NCD, results are inconclusive regarding activity: lying bouts were both found to decrease (<7 days) (Lowe *et al.*, 2019b) and increase (<7 days to 3 days) (Swartz *et al.*, 2020), and lying duration were both found to decrease (<6 days to 3 days) (Swartz *et al.*, 2020) and increase (<7 days) (Lowe *et al.*, 2019b). Finally, calves with inflamed navels show reduced lying time at day level after arrival at fattening farms compared to healthy calves (Studds *et al.*, 2018).

2.3.4.3 Changes in Other Parameters

Coughing which is a typical symptom of BRD can be detected using microphones (Ferrari *et al.*, 2010). Note that as opposed to activity and feeding behaviours, coughing has so far only been measured at group level. An increased coughing frequency was found to be correlated to BRD occurrence in group housed calves (Vandermeulen *et al.*, 2016; Carpentier *et al.*, 2018).

Changes in body temperature can be used to detected sick calves before clinical examination. BRD-diagnosed calves showed increases in orbital (eye plus one centimetre surrounding the eye) maximum temperature (Schaefer *et al.*, 2012) and reticulo-ruminal temperature, for example, - 136 h to - 12 h (Timsit *et al.*, 2011) and - 3.5 d (Voss *et al.*, 2016) relative to diagnosis. One important methodological consideration with thermometers is that recorded temperatures differ based on the body area that is investigated. For example, skin temperature was consistently 2 °C to 3 °C lower than the rectal temperature (Nogami *et al.*, 2013), while reticulo-rumen temperature was consistently 0.57 °C higher than rectal temperature (Timsit *et al.*, 2011). As long as these differences between recorded temperature and body temperature are consistent, this should not affect the detection of temperature increases due to diseases in calves. In calves diagnosed with NCD, temperature of the side flank and shoulder increased at least seven days prior to diagnosis (Lowe *et al.*, 2019b).

Changes in social behaviours were also detected in sick calves. Sick calves were found to show decreases in daily social grooming time and daily social lying time (lying within one body length of another calf) (Hixson *et al.*, 2018).

Some other behavioural parameters can be well recorded by sensors, but their potential in early disease detection is yet unknown. These include sucking behaviour (Kour *et al.*, 2018), rumination time (Rodrigues *et al.*, 2019), and play behaviour (Rushen and Passillé, 2012; Luu *et al.*, 2013; Größbacher *et al.*, 2020). Further research into the link between these parameters and disease is warranted.

As explained above, behaviour and physiology change with disease and these changes can be detected using sensors and algorithms. However, the particular behavioural or physiological parameter that is most accurate in detecting a diseased state, or is fastest at detecting a diseased state, will depend on the variations in the pathogenesis and potentially also the innate and adaptive immune response of the calves. Theoretically, 'behaviours that are less critical for immediate survival and primarily support long-term fitness are most affected by disease' (Weary *et al.*, 2009), such as play and exploratory behaviours Cramer *et al.* (2015). In practice, the type of diseases and the age of the animals also need to be taken into consideration as they might influence behavioural deviations. For example, in parasitized beef steers and BRD-infected dairy calves, changes in activity (i.e. lying, standing, and step counts) enabled a better disease detection than feeding behaviours such as frequency and duration of feeding and drinking behaviour (Szyszka *et al.*, 2012) and feed intake (Swartz *et al.*, 2017). In identifying NCD-infected calves and BRD-infected steers, however, feeding behaviours (i.e. the number of unrewarded visits to an automated milk feeder, DMI and bunk visit duration) permitted a more accurate detection of disease compared with activities such as lying and standing duration (Sutherland *et al.*, 2018; Kayser *et al.*, 2020). In addition, certain diseases result in behavioural changes that are easier to detect at an earlier stage. NCD-diagnosed calves, for example, displayed earlier and more consistent changes in feeding behaviours compared with BRD-diagnosed calves (Knauer *et al.*, 2017). Further research is hence needed into identifying the best, most sensitive behavioural and physiological parameters that can identify specific diseases or diseased state on a generic level.

2.3.5 Stage three: Information Integration - Outcomes of Models

To date, sensor fusion (i.e. two or multiple sensors) was applied in a number of studies (n = 9, Fig. 3), in which data from accelerometers, thermometers, and AFS are integrated into one model to identify diseases including BRD (Kayser *et al.*, 2020; Duthie *et al.*, 2021) and NCD (Sutherland *et al.*, 2018; Lowe *et al.*, 2019b). Information integration, however, means more than a multiple-sensor-tool. First, 'integration' does not mean accumulating all the data obtained from different sources. In the design of systems at stage three, redundancy needs to be reduced for a disease detection model. To reach this, data mining (Knight, 2020), which allows for a more complete understanding of different parameters in relation to disease occurrence, is a prerequisite. Data mining allows for the selection of the key parameters, the variation of which reflects health status with high accuracy. In this way by reducing the redundancy the number of sensors used and possibly attached to a calf will be reduced. Second, multiple data sources mean that sensor data are not the only sources of data. Economic insights, for example, were also suggested to be considered for the treatment decisions (Timsit *et al.*, 2011; Kayser *et al.*, 2019).

Given that many sensors and techniques are already commercially available, it is crucial to choose an appropriate sensor system when recoding certain parameters. For example, the combination of video cameras and sensors (including thermometers, accelerometers, or AFS), although popular for research (n = 5), seems impractical for on-farm settings. This might be due to the number of cameras required and the time-consuming process of analysing the video footage. However, artificial intelligence is able to identify physiology and behaviour of animals using video footages, for example, in Guo *et al.* (2020), allowing for high accuracy with less labour.

Therefore, 'information integration' means 1) selecting as few as possible meaningful parameters indicative of diseases when developing models (thereby avoiding redundancy or collinearity), 2) selecting the most appropriate sensors for recording these parameters. The integrated systems will give an alert when the current status of a calf deviates from its earlier patterns. Ideally, models at this stage includes a minimum number of sensors per animal, which is advantageous in terms of costs, maintenance labour but also maintaining the integrity, and freedom of movement of calves.

2.3.6 Stage four: Decision Support - Automation

At stage four, decision support means that the integrated system can, 1) identify which disease is occurring, 2) indicate whether to treat or not, and preferably 3) suggest which treatments to give, based on the developed model, and subsequent prognosis. Farmers can refer to the decision made by the system as support. To the authors' knowledge, no such systems are available for early disease detection in calves. An example of a stage four system in dairy cows is oestrous detection and automatic identification of the best way to inseminate the cow (Mottram, 2016). In the situation of early disease detection in calves, however, so far only alerts are available.

For the future, automation is crucial - decision support system with an easy-to-operate user interface is what farmers need for an easy identification of sick calves. Current models may give some form of alert, yet cannot give automatic decision support. Another important characteristics of such systems is the possibility for the farmers to enter feedback (e.g. was the identified individual truly ill with the proposed disease and was the treatment efficient) so that the system can continuously learn and adapt to the specific farming conditions. Knight (2020) suggested a business model that bridges information integration and decision support. In the provided business model, farmers are buying service from service providers. A service provider purchase the technologies from different developers, and provide the service of installation, maintenance, data collection, and data integration, therefore provide decision support to the farmers.

2.3.7 Introducing 'Resilience' Theory

Following the above four-stage approach, the decision-support systems are developed to detect diseases at an early stage and propose a treatment (or decision), but cannot predict the likelihood of a clinically healthy animal to becoming diseased in the near future, i.e. its predisposition to diseases. In a paper discussing sensor technologies in dairy farming, the author argued that 'the focus is on improving overall husbandry, rather than 'solving' specific disease problems' (Knight, 2020). The same focus should apply to the dairy and veal industry as well. We therefore introduce 'resilience' theory, through which the developed system might be able to quantify resilience of individual animals, thereby identifying animals in a low-resilience state. This potentially allows for early intervention in the husbandry system, whereby the environment or management in such a way that low-resilient individuals and the herd as a whole can maintain relatively healthy states.

Resilience in farm animals has been defined as 'the capacity of the animal to be minimally affected by a disturbance or to rapidly return to the physiological, behavioural, cognitive, health, affective and production states that pertained before exposure to a disturbance' (Colditz and Hine, 2016). Calves falling sick can be equalled to a complex system transiting from one stable state (healthy) to another (unhealthy), with the return to the original state being more difficult than the simple cancellation of factors that caused the change in state. Such shifts in complex systems have been termed 'critical transitions' or 'tipping points' (Scheffer *et al.*, 2009). When such complex systems are close to tipping points, the recovery rate of that system from small perturbations becomes very slow, and this is known as 'critical slowing down' (**CSD**) (Scheffer, 2012). For example, a cow showing 'CSD' before parturition, in this case using an accelerometer to assess activity (e.g. low average eating time, a disturbed circadian rhythm, and variance in ear temperature), is likely to develop periparturient disorders (van Dixhoorn *et al.*, 2018). CSD, which can be revealed through dynamic aspects of sensor data, is here seen as an increase in variance in the activity data, hence a loss of regularity. CSD, therefore, reflects a loss of resilience (Schffer *et al.*, 2009; Scheffer, 2012). In still clinically healthy individuals, CSD reflects the animal's vulnerability to pathogens prior to the disease, and hence reflects a state of low resilience. Identifying CSD in sensor data patterns of 'low resilient' individual animals, enables timely change to the environment of this animal in an attempt to increase resilience (e.g. remove stressors, improve nutrition).

Current sensor tools focus on detecting early stages of disease, while sensor technology already allows us to analyse the dynamics of physiology and behaviour with high accuracy. Advanced analytical tools can estimate resilience status from the micro-recoveries in the data flow (Scheffer *et al.*, 2018). These tools invite a fundamental rethinking of our approach towards a pro-active rather than reactive calf health management.

2.4 Conclusion

This review summarized the literature on sensor systems so far studied in the context of health monitoring in calves between 2009 to 2021, and revealed the current stage of development by categorizing each study based on a four-stage system stages (sensor technology, data interpretation, information integration, decision support). Our literature search demonstrated that most studies up to now are at stage one (sensor technique) or stage two (data interpretation), a few studies are at the beginning of stage three (information integration). Accelerometers, IRT cameras, microphones, 3D cameras can be accurate in measuring behavioural and physiological parameters in calves, among which deviations in behaviours (e.g. feeding, lying, and social behaviours), activity, and body temperature can be detected prior to the clinical examination and are promising for developing algorithms. To develop a health detection model with a minimal number of sensors, it is crucial to select appropriate sensor systems, which can record the most relevant parameters that show clear changes in response to diseases in calves. Clear gaps in research include stage three (information integration) and stage four (decision support) systems, as well as forecasting methods via the identification of low resilience animals.

2.5 Tables

Table 1 Gold standards of studies at stage two and three

No.	Reference	Stage	Gold standard		
			Clinical examination	Blood analysis	Other
1	Borderas *et al.* (2009)	2	Yes (daily)		
2	Timsit *et al.* (2011)	2	Yes (twice daily)	Yes	
3	Schaefer *et al.* (2012)	2	Yes (daily)	Yes	
4	Moya *et al.* (2015)	2	Yes (frequency information not available)		Carcass information, lung lesions
5	Wolfger *et al.* (2015a)	2	Yes (twice daily)	Yes	
6	Jackson *et al.* (2016)	2	Yes (at least twice daily)		BW
7	Johnston *et al.* (2016)	2	Yes (modified Wisconsin calf health scoring chart: twice weekly in pre-weaning and weaning periods and once weekly in post-weaning period)	Yes	
8	Pillen *et al.* (2016)	2	Yes (daily)		Depression score
9	Vandermeulen *et al.* (2016)	2	Yes (Wisconsin calf clinical respiratory score: at least twice weekly in pre-weaning period and once weekly in post-weaning period)	Yes	
10	Voss *et al.* (2016)	2	Yes (at least twice daily)		
11	Knauer *et al.* (2017)	2	Yes (Wisconsin calf clinical respiratory score: daily)	Yes	Calf enrolment, treatment record, morbidity and mortality data
12	Swartz *et al.* (2017)	2	Yes (Wisconsin calf health scoring chart: twice daily)		
13	Carpentier *et al.* (2018)	2	No examination	Yes	

14	Knauer *et al.* (2018)	2	Yes (Wisconsin calf clinical respiratory score: daily)		Calf enrolment, treatment record, morbidity and mortality data
15	Oliveira *et al.* (2018b)	2	Yes (daily)	Yes	
16	Shane *et al.* (2018)	2	Yes (daily)		
17	Studds *et al.* (2018)	2	Yes (twice weekly)		
18	Kayser *et al.* (2019)	2	Yes (twice weekly)		BW
19	Swartz *et al.* (2020)	2	Yes (Wisconsin calf health scoring chart: twice weekly)		
20	Hanzlicek *et al.* (2010)	3	Yes (three times daily)	Yes	
21	Szyszka *et al.* (2012)	3	Rectal temperature (d 0, 13, 15, 17, 20, 27, and 31); fecal samples (d 0, 13, 15, 17, 20, 27)	Yes	BW
22	Toaff-Rosenstein *et al.* (2016)	3	Yes (daily)		Necropsy
23	Toaff-Rosenstein and Tucker (2018)	3	Yes (daily)		
24	Hixson *et al.* (2018)	3	Yes (Wisconsin calf health scoring chart: twice daily)		
25	Sutherland *et al.* (2018)	3	Yes (daily)	Yes	BW
26	Lowe *et al.* (2019b)	3	Yes (daily)		
27	Kayser *et al.* (2020)	3	Yes (twice daily)	Yes	
28	Duthie *et al.* (2021)	3	Yes (modified Wisconsin calf health scoring chart: daily)		

Table 3 Performance of algorithms and models

No.	References	Features	Performance							
			Se[1] (%)	Sp[2] (%)	Accuracy (%)	PPV[3] (%)	NPV[4] (%)	Other parameters	Days prior (best)	Days prior (least)
1	Jackson *et al.* (2016)	Feeding behaviour							-14.2	-1.3
2	Kayser *et al.* (2019)-univariate factors	Feeding behaviour			48.7-80.1				-10.2	-0.6
3	Wolfger *et al.* (2015a)	Feeding behaviour							-7	
4	Lowe *et al.* (2019b)	Feeding behaviour, lying behaviour, body temperature							-7	-4
5	Swartz *et al.* (2020)	Activity, lying behaviour							-7	-6
6	Jackson *et al.* (2016)	DMI							-6.8	
7	Timsit *et al.* (2011)	Reticulo-rumen temperature						0.91 (r), 0.82 (r^2)	-5.7	-0.5
8	Sutherland *et al.* (2018)	Feeding behaviour, lying behaviour							-5	0
9	Pillen *et al.* (2016)	Activity							-5	-1
10	Kayser *et al.* (2020)	Feeding behaviour			0.61-0.89				-4.5	
11	Kayser *et al.* (2020)	Rumen temperature			0.78				-4.5	
12	Sutherland *et al.* (2018)	Feeding behaviour							-4	0
13	Knauer *et al.* (2017)	Feeding behaviour, activity							-4	7
14	Voss *et al.* (2016)	Reticulo-ruminal temperature	71	98		86	98	0.855 (area under curve)	-3.5	
15	Moya *et al.* (2015)-model 33	Feeding behaviour	66.7	58.3	62.5				-3.1	
16	Moya *et al.* (2015)-model 66	Feeding behaviour	75	50	50				-3.1	
17	Knauer *et al.* (2018)	Feeding behaviour	56.4	49.5		66.6	49.5		-3.1	
18	Knauer *et al.* (2018)	Feeding behaviour	70.9	32.9		65.3	38.7		-3.1	
19	Knauer *et al.* (2018)	Feeding behaviour	74.9	27.1		64.6	37.4		-3.1	
20	Johnston *et al.* (2016)	Feeding behaviour							-3	
21	Oliveira *et al.* (2018b)	Feeding behaviour							-3	4
22	Duthie *et al.* (2021)	Feeding behaviour, activity							-3	-1
23	Moya *et al.* (2015)-model 14	Feeding behaviour	58.3	83.3	70.8				-2.4	

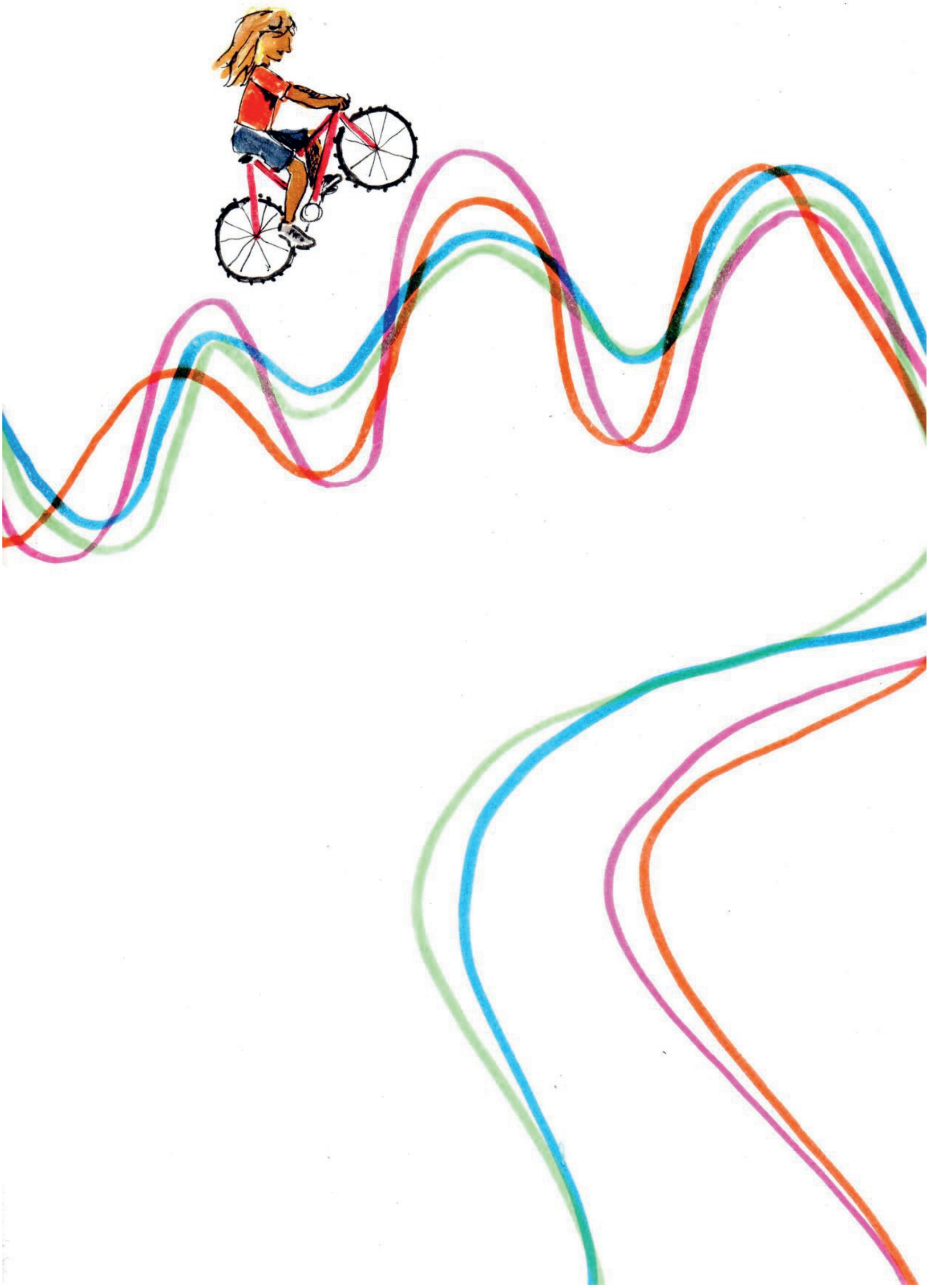
24	Kayser *et al.* (2019)-multivariate factors	Feeding behaviour			84			-2.1	-2
25	Shane *et al.* (2018)	Social network patterns			17.9-100	<10	>90	-2	0
26	Swartz *et al.* (2017)	Behaviour, activity						-2	
27	Sutherland *et al.* (2018)	Feeding behaviour						-2	0
28	Sutherland *et al.* (2018)	Lying behaviour						-2	0
29	Toaff-Rosenstein and Tucker (2018)	Rectal temperature						-2	
30	Moya *et al.* (2015)-model 3	Feeding behaviour	50	100	75			-1	
31	Oliveira *et al.* (2018b)	Feeding behaviour						-1	1
32	Toaff-Rosenstein and Tucker (2018)	Feeding behaviour						0	

[1] refer to sensitivity.

[2] refer to specificity.

[3] refer to positive predictive value.

[4] refer to negative predictive value.



Chapter 3 Activity patterns of healthy calves housed in large groups

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Abstract

Young calves are susceptible to disease. Studies indicate that calf activity often changes prior to a clinical diagnosis. Accelerometers can monitor activity continuously, offering an opportunity for early detection of disease in individual calves, based on deviation from 'normal' activity patterns. This requires the prior understanding of activity patterns in healthy calves. This study aimed at describing the normal activity patterns of healthy group-housed calves. Holstein and crossbred calves (n=231; 17 ± 4 d of age at arrival) were housed in six large pens. Milk replacer was available via automated milk feeders twice or three times daily (at around 4h30, 11h00 and 15h30, each period of milk availability lasted about 6h). Calves had ad libitum access to starter. Accelerometers were fastened to one of the front ankles of each calf. High frequency (sum of every 15min) activity data were continuously recorded from 6 to 28 weeks of age. Clinical examination was carried out twice per week by trained staff between 8 to 25 weeks of age, whereby any symptom of disease (e.g. nasal discharge; 15 variables in total) was scored a 1, 2 or 3 based on the severity, and subsequently summed to reach a total 'health score'. A calf day was defined as a sick day when either: the total health score was ≥ 5, the temperature was ≥ 39.5, or diarrhoea was detected. All calf days defined as sick, and between two healthy diagnoses, were removed from the dataset. Generalized additive models with a Gaussian response were used to estimate daily group patterns of 'being active' and 'being inactive' per week, corrected for trends over time/age. From these activity patterns, the following features (per week) were extracted from the model: number of peaks, time (of the day) at which peaks occurred, the height (i.e. absolute value) of each peak, and the proportion of the night activity. The results showed that normal activity patterns can be described using the above features. The number of peaks in activity went from 4 to 3 over the fattening period, with most peaks corresponding to new milk availability times. A peak in activity was consistently observed prior to dark. Night-time activity was consistently around 20% between 8 and 20 weeks of age and gradually increased between 21 and 25 weeks of age. A leave-one-out analysis showed a medium accuracy of using the fitted model to predict activity patterns of a group as well as individual calves. The performance of the model was moderate indicating that most calves deviate in some way from this average pattern. The next step is to identify which factors lead to individual differences between calves and to develop models that have a high performance in detecting deviations from normal which are indicative of health or welfare issues in calves.

Keywords: accelerometer, activity, disease, health monitoring, veal calves

3.1 Introduction

The Netherlands is the biggest veal producer in EU, accounting for 36% of the total production in 2020 (Berkhout *et al*., 2021). With over one million veal calves being kept in around 1,600 fattening farms[2], the Dutch veal sector produces 1.6 to 1.7 million calves per year (Berkhout *et al.*, 2021). In the Netherlands, veal calves are typically transported from the dairy farm to the veal farm (via an assembly centre) between 14 and 35 days of age. Veal calves stay at the fattening farm until they reach their slaughter weight, which for white veal calves is typically around 225 kg at average 25 weeks of age (Berkhout *et al.*, 2021). During the veal fattening period, one main problem is the high morbidity and mortality (Pardon *et al.*, 2013), leading to high use of antimicrobials (Pardon *et al.*, 2013) and high resistance to antimicrobials in bacteria within this sector (Yang *et al.*, 2020). Factors likely to be responsible for this high morbidity and mortality include: an abnormal navel, dehydration, presence of a sunken flank, arriving in the summer (Renaud *et al.*, 2018a), higher numbers of calves transported to the same farm (Sandelin *et al.*, 2022), larger age variation in the same arrival batch (Sandelin *et al.*, 2022). Factors responsible for high antimicrobial usage include: beef breed (higher use compared to dairy and crossbreeds), calves arrival in winter months (higher use compared with arrival in April and May), and veal company (Bokma *et al.*, 2019).

When multiple sick calves are identified in a barn, group treatments might be applied given through the automated milk feeders (**AMFs**), leading to non-specific use and hence higher use of antimicrobials. To safeguard animal welfare and human health, it is imperative that farmers are able to identify sick calves, an early stage of disease, allowing timely and individual treatment application. However, current health monitoring is carried out on many animals by farm staff in a limited amount of time, which cannot guarantee every sick calf is identified at an early stage of disease, where symptoms are possibly difficult to spot.

To identify a sick calf at an earlier stage, precision livestock farming (**PLF**) tools might provide support in addition to the conventional health check by farm staff. PLF tools able to identify disease in individual animals could provide alerts to farm staff, enabling more focused health checks by these staff and possible timely, individual treatments and separation of diseased animals, reducing further spread of diseases. An example is the application of accelerometers.

[2] Source: Landbouw; gewassen, dieren, grondgebruik en arbeid op nationaal niveau (cbs.nl)

Accelerometers attached to a limb monitor calf activity, and have been shown to have potential in disease detection such as bovine respiratory diseases (**BRD**, Ramezani Gardaloud *et al.*, 2022) and neonatal calf diarrhoea (**NCD**) in calves (Goharshahi *et al.*, 2021). Before defining an algorithm for early disease detection, it is important that we understand the activity patterns of healthy calves. To the authors knowledge, no study has previously described in detail the daily activity patterns and trends of healthy group-housed calves. The objective of the current study was therefore to define these 'normal' patterns of activity in healthy group-housed veal calves using generalized additive models. In particular we answer the following questions: 1) What does the daily activity pattern of healthy calves typically look like? 2) How do activity patterns of healthy calves change over the fattening period (from 8 to 25 weeks of age)?

3.2 Materials and Methods

The study was approved by the Central Committee Animal Experiments (Centrale Commissie Dierproeven, CCD; beschikking 2655) in the Netherlands.

3.2.1 Animals and Management

The study was carried out between July 2021 and January 2022 on a Dutch commercial veal farm. Two-hundred and thirty-one Holstein and crossbred calves (2 weeks of age at arrival) from the same batch were included. Calves were kept individually in so-called 'babyboxes' inside the group pens for the first four weeks following arrival and were thereafter released into six pens (9.15 x 7.5 m per pen, N = 38 ± 2 calves per pen, mean ± SD). The babyboxes were 110 x 80 cm whereby calves were able to turn around, and these boxes permitted tactile contact with neighbouring calves, as well as visual and auditory contact with calves in the same pen. Calves were re-grouped three times (i.e. last week in September, second week in October, first week in November) during the fattening period based on body size by farm staff. Calves were kept in the same barn during the entire fattening period. The ventilation system in the barn used a combination of electronic ventilation fans and side curtains. Each pen in the group housing was equipped with enrichment in the form of several suckler teats (± 6 mounted on the wall and ± 6 in a bucket hanging from the roof), one calf scrubbing brush, one mineral block and one large yellow skippy ball hanging from the roof. Pens were equipped with rubber coated slatted flooring. Light was on when farm staff was present. Group and individual medicine treatments were administrated and recorded by farm staff. Calves received herd level treatment at arrival (ornithine transcarbamoylase, 5d), 1, 6, 7 week on arrival (Doxycycline, 5d), 2 weeks on arrival (Tilmoved, 5d), 3 weeks on arrival (Ampisol, 5d). Calves received herd level treatment in the form of sodium salicylate (1g/50kg; 3-7d) at 0, 1, 2, 3, 4 ,5, 6, and 16 weeks on arrival. All herd level treatments were supplied in the milk replacer through the AMF. Sick calves were treated with antibiotics and (or) anti-inflammatories. Calves were slaughtered at 27 to 28 weeks of age.

Fig. 1 Set-up of the house[1]

[1]Left, individual 'babyboxes'; right, group housing.

3.2.2 Feeding

During individual housing, calves were bucket-fed with 4L of milk replacer twice per day (2L each meal) at approximately 8h00 and 18h00, and had ad libitum access to calf starter. During group housing, calves were fed milk replacer through an AMF (n = 6, Förster-Technik GmbH, Engen, Germany). A new allowance of milk replacer was available to the calves via the AMF twice daily (between week 8 and 20, at around 4h00 and 15h30, each meal lasted about 6h; from week 21 onwards, at around 4h00, 11h30, and 16h30, each meal lasted about 5 to 6 hours). The average amount of milk replacer allowance increased from 6 L to 14 L per week gradually over the entire fattening period (Table 1). Water was supplied 6 h per day in two periods (from 8h00 to 11h00, from 20h00 to 23h00) through an automatic water drinker. Calves had ad libitum access to starter through one shared trough per group, Calf starter consists of straw and concentrates. Roughage contents changed over time and were mixed with approximately 15% finely chopped straw. Concentrate contents were gradually mixed on overlapping days (roughage concentrate contents: day 1 to 35 on arrival - protein:12.5%, fat: 4.5%, crude fibre: 7.7%. Day 14 to 80 on arrival - protein: 17.0%, fat: 4.0%, crude fibre: 5.3%. Day 70 onwards on arrival - protein: 14.0%, fat: 4.0%, crude fibre: 5.3%).

3.2.3 Activity

Accelerometers (SmartTag, Nedap N.V., Groenlo, the Netherlands) were equipped to one of the front ankles of each calves on the day before they were released into their groups, approximately six weeks of age. High frequency activity data (sum of every past 15 min) of lying time, standing time, walking time, number of lying bouts, step count were continuously recorded throughout the fattening period in individual calves (6 to 28 weeks of age).

3.2.4 Health Score

A health protocol was created (Table 2) based on the Calf health scorer of the University of Wisconsin-Madison (available at https://www.vetmed.wisc.edu/fapm/svm-dairy-apps/calf-health-scorer-chs/) and the Welfare Quality Protocol for veal calves (Welfare Quality®, 2009). Clinical examination was carried out twice per week and were performed by a trained staff (DS) between 8 and 25 weeks of age. Intra-observer reliability was verified by repeated scoring of calves during the past batches of the experiment (100% agreement was noted). A sick calf was defined meeting either of these categories: 1) a total score ≥ 5, 2) temperature score = 1, 3) diarrhoea score = 1.

3.2.5 Statistical Analyses

3.2.5.1 Data preparation

Two-hundred-and-thirty-one calves were included for the statistical analysis. The raw activity data for 231 calves are available. Activity data were stored and organized in excel spreadsheets (version 2016, Microsoft Corp., Redmond, WA, RRID:SCR_016137). Further pre-processing and statistical analyses were performed using the R statistical software (version 4.3.0; R Core Team, 2022) and RStudio environment (version 2023.03.1; RStudio Team, 2020). Before analysis, the calves with missing activity data for a period longer than a day, and that are therefore sick for an extended period of time, were removed from the dataset. Furthermore, the activity data of animals that were declared sick during the course of the study were excluded for the duration of their illness, as these animals are likely to exhibit behaviours that deviate from their normal pattern. The period of sickness is defined as the time between the last visit (prior to the visit that declared the animal sick), where the animal was not declared sick, and the next visit (following the visit that declared the animal sick), where the animal was not declared sick. The final activity dataset used for statistical analysis comprised data on 218 calves over a period of 18 consecutive weeks. To characterize the activity pattern of the group of 218 calves over time using the statistical model described below, the numerical variables “week”, “day” and “minute”, that respectively represent the number of weeks from the start of the study, the number of days from the start of the study and the number of minutes from the start of the day, were created. These three variables represent different scales of time and are used as explanatory variables to describe and predict the activity of the calves. The activity of calves is measured by the numerical variables “lying time”, “standing time” and “walking time”, that represent the number of minutes, out of a 15-minute window, that a calf has spent lying, standing or walking. Because these three numerical variables measuring activity are related (the value of one is a linear combination of the other two), there were recoded into a single categorical variable “activity”, with categories “lying”, “standing” and “walking”. Our original goal was to employ multinomial logistic regression to predict the categorical “activity” using the three numerical time variables. However, due to large size of the activity dataset, fitting this complex model is computationally infeasible. Therefore, we transformed the three-category variable “activity”, with categories “lying”, “standing” and “walking”, into a two-category variable. The relabelled categories became “inactive” and “active” by combining the original “standing” and “walking” categories. This modification allowed us to use a logistic regression model that is computationally feasible.

3.2.5.2 Model

The statistical model used to describe the activity pattern of the group of calves is provided in Equation (1). This model uses the two-category variable “activity” as response variable and the three numerical time variables “week”, “day” and “minute”, as explanatory variables. To describe in a flexible way the activity patterns, the effects of the three times variables were modelled with cubic splines, which are non-linear and smooth functions. Specifically, a smooth function f_0 was used for “day” to describe globally the activity patterns and smooth functions f_j for “minute” were used to describe the activity patterns on a weekly basis. The factor “pen” (α_q) was included in the model as a standard fixed effect. Denoting by $y_{ijkl} \in \{0,1\}$ the observed response (0 for “inactive” and 1 for “active”), the logistic model is:

$$\begin{cases} y_{ijkl} \sim Bern(m_{ijkl}, p_{ijkl}) \\ logit(p_{ijkl}) = log\left(\frac{p_{ijkl}}{1-p_{ijkl}}\right) = \mu + \sum_{q=1}^{6} \alpha_q + f_0(x_k) + f_j(x_l) \end{cases} \quad (1)$$

Here, $Bern(m, p)$ denotes a Bernoulli distribution with number of trials m and probability p. Furthermore, p_{ijkl} represents the probability that calf $i \in \{1, \dots, 218\}$ is active in week $j \in$

$\{1, \ldots, 18\}$, day $k \in \{1, \ldots, 126\}$, and minute window $l \in \{1, \ldots, 96\}$ (there are 96 15-minute windows per day), whereas α_q denotes the effect of pen $q \in \{1, \ldots, 6\}$ (the contrast $\alpha_1 = 0$ was used to ensure model identifiability).

The above model is a generalized additive model (**GAM**) and was fitted using the function *bam* (Wood *et al.*, 2015; Wood *et al.*, 2017; Li and Wood, 2019) of the R package *mgcv* version 1.8-42 (Wood, 2011), which is designed to fit GAM models to very large datasets, as in our case.

Our interest lies in the estimated smooth curves of the logistic model that describe activity patterns, but also in summary statistics of these curves such as the number, time and height of peaks, and the proportion of night activity (before 4am and after 9pm). These summaries were extracted from the fitted model.

3.2.5.3 Leave-one-out analysis

As it is not possible to obtain variance estimates for the extracted summary statistics directly, we conducted an leave-one-out analysis (**LOO**). This consisted in iteratively removing one calf from the dataset, refitting the logistic model using the data of all other calves, and extracting summary statistics from the estimated curves. This process was repeated for each calf in the dataset. The variances of the leave-one-out summary statistics were used as estimates of the variance of the summary statistics on the complete activity dataset.

Although the prediction of calf activity is not the main focus of the present paper, the LOO was also used to assess the out-of-sample prediction performance of the model. Each fitted model was used to predict the activity status of the calf that was left out. A data point is classified as "active" when its estimated probability of being active is greater or equal than $t = 0.5$. Then, performance is assessed by comparing predicted and observed classifications by reporting the sensitivity, defined as the proportion of predicted active states among truly active states, and the specificity, that is defined as the proportion of predicted inactive states among truly inactive states. Instead of reporting the sensitivity and specificity based on a single value for the threshold t, the receiver operating characteristic (**ROC**) curves that display sensitivity as a function of 1 - specificity for a range of values for t are provided. The area under the ROC curve (**AUC**) is a numerical summary of this curve. ROC curves and AUC are reported for each left-out calf of the LOO and overall.

3.3 Results

The histogram of the distribution of probability of being active over the fattening period (Fig. 2) showed that between 8 to 25 weeks of age, healthy calves spent on average 60.7% of their daily time being inactive (i.e. lying) and 39.3% of their daily time being active (i.e. walking and standing). Average activity of being active and being inactive per week were summarised in Table 3 (the full summary of the weekly average of daily activity can be found in Appendix 1). At 8 weeks of age, healthy calves spent on average 68.5% of their daily time being inactive and 31.5% of their daily time being active. As the calves grew older, they spent gradually less time being inactive (63% at 25 weeks of age) and consequently gradually more time being active (37% at 25 weeks of age). The proportion of night activity accounted for around 20% of the total activity between week 8 and week 20, and increased from week 21 till reach to 27% of the total activity on week 25. The ROC curve of the LOO on group activity patterns of being active has an AUC of 0.67 (Fig. 3). The ROC curves of the LOO for each calf are presented in Fig. 4.

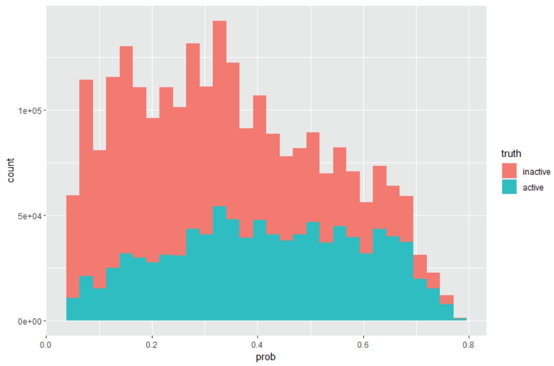

Fig. 2 Histogram of the distribution of probably of being active over the fattening period

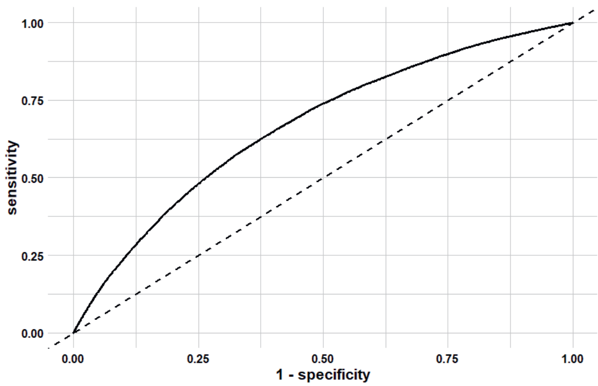

Fig. 3 ROC curves of the LOO analysis on group activity patterns of being active

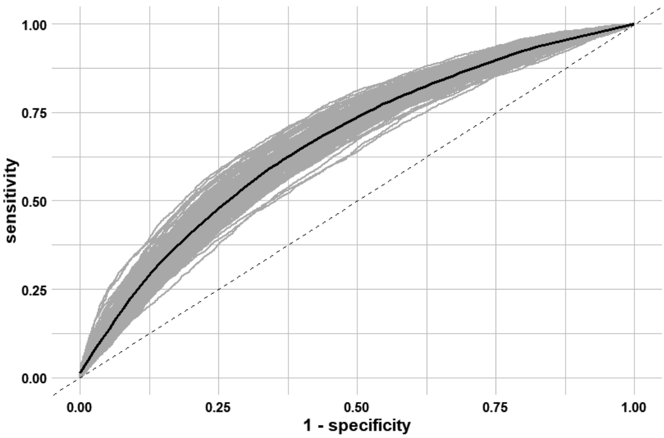

Fig. 4 ROC curves of the LOO analysis on individual activity patterns of being active

Activity pattens between week 8 and 25 were plotted per week with smooth curves (Fig. 5). Four features (i.e. number of peaks, height of each peak, time of each peak, the proportion of night activity) were extracted from these group curves per week and these are shown in Table 4. On average, the activity of healthy group-housed calves showed four peaks between 8 weeks of age (at 4h48, 10h33, 16h05, and 21h07), 20 weeks of age (at 5h31, 10h48, 16h19, and 21h21). In contrast, the activity of healthy group-housed calves showed only three peaks between 21 weeks of age (5h31, 11h02, and 21h07) and 25 weeks of age (5h46, 12h29, and 21h36). The timing of each peak shifted gradually to later times as calves grew older, except the first peak at 9 weeks of age, the third peaks at 10 and 17 weeks of age, and the fourth peak at 17 weeks of age. In terms of the height of peaks, which indicates a higher probability for calves to be active at this time, there was a shift over time as to which of the peaks was the highest. Between 8 and 12 weeks of age, the fourth peak of activity was the highest compared with other weeks (based on means comparisons). At 13 weeks of age the second and fourth peaks were the highest. Between 14 and 21 weeks of age, the second peak was the highest. Between 22 and 25 weeks of age, the third (and last) peak was the highest. The proportion of night activity (defined as the time between 21h00 and 4h00) was relatively stable between 8 and 21 weeks of age except at 17 weeks of age where a slight drop in night activity was identified. The proportion of night activity increased between 22 and 25 weeks of age.

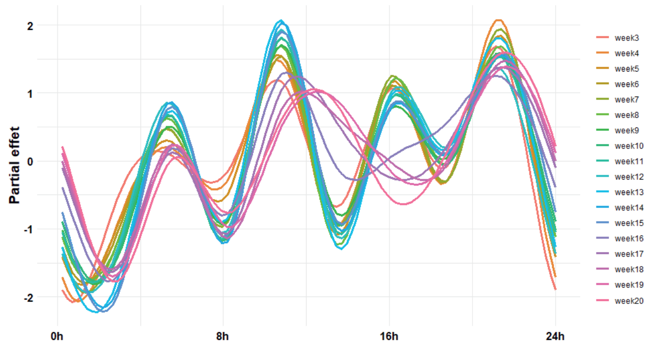

Fig. 5 Smooth curves of group activity patterns between week 3 and week 20 of attaching acceleromaters[1]

[1]Week 3 equals to an average 8 weeks of age, week 20 equals to an average 25 weeks of age.

3.4 Discussion

The aim of this study was to describe the daily activity pattern of healthy, group-housed calves and changes in these activity patterns across the fattening period. To the authors' knowledge, this is the first article describing the normal activity patterns of young healthy veal calves housed in large groups. The rationale behind this study, other than knowledge acquisition in itself, is that deviations from healthy patterns of behaviour, for example activity, may be indicative of disease, or other negative experiences such as social stress, in farm animals (Millman, 2007), which means that identifying sick calves first requires the understanding of healthy, normal patterns of behaviour. In particular, there may exist large individual variation in activity patterns within groups of healthy calves and activity patterns may be affected by the specific management routines implemented at the farm (Bus *et al.*, 2021). The understanding and prediction of group patterns in healthy calves is also valuable as it might provide a reliable trend of how the normal activity of calves changes across the fattening period: the normal activity patterns could be used as the benchmark for developing a disease detection or health monitoring model for individual calves.

To describe the group activity patterns in healthy calves, we drew smooth curves of the activity for each week of the fattening period. These smooth curves allowed us to describe the activity patterns across multiple dimensions via so-called 'extracted features'; in this case: the number of peaks in activity, the time at which the peaks took place, the height of the peaks, and the proportion of night activity. This is a new approach as previous studies typically describe activity either in minutes per day (e.g. Omontese *et al.*, 2022), or display average calf activity (standing or lying) across the day on a graph, without extracting key features (Webb *et al.*, 2012, 2014, 2015: based on direct manual observations). The added value of the smooth curves is that they represent the expected increase in variables for specific moments of the day when all other parameters in the model are fixed (partial effects are adjusted or scaled variables adjusted for all other variables, e.g. pen, in the model including intercept). In the results, we presented one of the two opposite activity patterns, i.e. activity of 'being active', as opposed to 'being inactive'. Following our two-category activity definition, the percentage of the activity of 'being active' equals to 1- (the percentage of the activity of 'being inactive'), which means the smooth curves of the two activities have exactly opposite trends, therefore showing one of them is enough to clarify the pattern and changes in this pattern over time. The following discussion therefore uses the term 'activity' to represent the behavioural state of 'being active'.

We observed a stable number of four peaks of activity between week 8 and week 20 on average, followed by a stable number of three peaks between week 21 and 25. Between week 8 and 20, milk replacer was made available by the AMF twice daily (at around 4h00 and 15h30, each meal timeslot lasting approximately 6h), and was increased to three times daily from week 21 onwards (at around 4h00, 11h30, and 16h30, each meal timeslot lasting approximately 5 to 6 hours). The number of peaks, therefore, does not follow the number of milk feeding timeslots, as expected: an increase in milk feeding timeslots was expected to lead to a higher number of peaks of activity, but instead we noted a decrease in the number of peaks. Since the number of peaks in the weeks with three milk feeding timeslots corresponds exactly to the number of activity peaks displayed by the healthy calves, this could point to a better ability of calves to focus their activity around feeding moments, making them more efficient in the use of their time. Possibly young calves are less able to do so as they have a smaller stomach, or possibly a frequency of two milk feedings per day is simply too far from the voluntary milk feeding frequency of calves, which seems to be around 7 to 8 feedings per day (Webb *et al.*, 2014), leading the calves to visit the AMFs more frequently. In terms of height of peaks, the height of peaks showed that calves become more and more active across the day, from morning to evening, which is consistent with previous research (Alawneh *et al.*, 2020). The respective height of peaks increased as calves grew older, especially the first and the second peaks between week 8 and 20. This suggested that the calves' activity level increased in general as calves grew older. The first peak in all weeks occurred approximately one hour after the starting of the first session of the milk replacer supply, with a constant timing of peaks in most of the weeks, i.e. 5h17 (between week 8 and 20) and 5h31 (between week 21 and 25), suggesting that the first peak is closely linked to the timing of milk feeding. The sudden drop of the height of first peaks between week 21 and 25 was speculated to be caused by the extra milk feeding timeslot implemented from week 21 onwards. Calves as a result had higher milk replacer intake during the day and were therefore potentially less hungry and hence less eager to access to the AMFs when the first feeding session started,, around 4h in the morning, which is reflected by lower peaks. Similarly, between week 8 and week 20: the third peaks occurred right after the starting of the afternoon milk timeslot (15h30), and the relative stable height of the third peaks indicated the normal activity level caused by the feeding; the difference of heights between the first and the third peaks narrowed down gradually as calves grew older, till the third peaks reached to similar heights as the first peaks at week 19 and week 20, suggesting that the calves were more eager to access to AMFs in the morning as they grew older. Our results were in line with recent studies reporting, that the activity patterns were related to the feeding time in calves (Omontese *et al.*, 2022; Giannetto *et al.*, 2023).

In our study, most management procedures were taken place in the morning after the supply of the solid feed (at around 08h30), including daily inspection by the farmers, cleaning the house and maintenance, visits by the veterinaries, administrating individual treatments, etc. The second peaks between week 8 and 20 had stable time of peaks (around 10h30), the height of peaks increased gradually, with much higher heights than the first and the third peaks at corresponding weeks. This suggested that the second peaks should not (solely) be caused by the milk feeding, with no new milk timeslot occurring at this time, but might to a large extent be caused by the farm management activities and calves' natural need to move during the day. From week 21 onwards, calves had an extra milk replacer supply in the morning (at round 11h00 to 11h30), which may explain the second peaks in terms of time of peaks (between around 11h00 and 12h30) and height of peaks (have similar height of peaks as the third peaks between week 8 and 20) of the between week 21 and 25. We noticed a gradual increase of the first and the second height of peaks between week 8 and week 20, suggesting that the activity levels increased as calves grew older; the following drop of the first and the second peaks between week 21 and week 25 might indicated that calves were less active when having enough milk intake. Between week 21 and 25, we noticed the disappearing of the original third peaks (observed between week 8 and 20) in the late afternoon (around 16h00). We speculated that this might be caused by the extra milk supply in the late morning (11h30). With three milk timeslots instead of two (each session lasted between 5 to 6 h), calves may have had sufficient milk intake and short waiting time in between the milk timeslots, especially between the second and third milking session. As a result, calves had access to AMFs with longer time window and could drank more milk, we assume that this avoid the "rush hour" at the starting of the milking sessions with a restricted feeding routine.

We identified a relative stable final peak just before dark (between 21h07 and 21h36) and far from any kind of feeding or farm management timeslot. The heights of peaks (i.e. the fourth peaks between week 8 and 20, the third peaks between week 21 and 25) were higher than the putative milk-related peaks (i.e. first peaks between week 8 and 25 and third peaks between week 8 and 20), and closer in terms of height to the second peak apparent between week 8 and 25 on the respective weeks. We speculated that the last peaks were due to calves' need to express their natural behaviours, e.g. grazing at night (Kilgour, 2012) and play behaviour before dark (Jensen *et al.*, 1998). A similar peak in calf activity just before dark, specifically around 20h00 and 22h00 was also reported by Webb *et al.* (2014), in terms of percentage of calves standing at a given time. In this study, we did not observe the behaviour of our calves manually. However, our pilot study (with video footage, not reported here) observed a peak of play behaviour in young calves in the evening. To further study the last peaks, we recommend incorporating behaviour recording as reference.

We observed a relative constant night activity level (between 21h00 and 04h00), with a gradual increase in the last four weeks of the fattening period, when the calves have become much larger and consequently the space available in the pen much lower. This may result over time in large groups of calves becoming seemingly more active throughout the fattening period as a result of increasing disturbances between animals linked to limited space. Alternatively, since the change in night-time activity was detected by our model from week 21 onwards, it might hence be linked to the changing of the milk feeding routine: the extended milk replacer feeding time and the increased milk intake and might result in higher level activities of calves during the night. However, this warrants further research. We also identified the deviations of time of peaks on some weeks compared to the weeks prior and after, e.g. the timing of the first peak in week 14, the third time of peak on week 10, and the fourth time of peak on week 17. To explain these deviations require further analysis of the dataset, combining the feeding behaviour obtained from AMFs and the detailed farm management activities registered in the logbook.

A medium AUC of the LOO was displayed from our fitted model predicting a calf (and the group) being active. The predictive model had a medium accuracy (0.646) in its prediction of whether a calf was active or not at a given time, with a low sensitivity (0.355) and high specificity (0.834), suggesting that the predicted activity of 'being active' accounted for a low percentage of the truly activity of 'being active' in calves (i.e. low sensitivity), while the predicted activity of 'being inactive' was close to the true inactive activity (i.e. high specificity). The high specificity of the current model might be useful for further detecting a sick calf because the activity of being inactive (i.e. lying time) changes in a sick calf (Lowe *et al.*, 2019b, Swartz *et al.*, 2020). However, activity of 'being active' also changes in a sick calf, e.g. standing time (Pillen *et al.*, 2016). Further work is needed to improve the accuracy, especially the sensitivity of the model in its prediction of whether an individual calf is active or not. In a sick calf, we expect to identify the missing or the reducing of the features compared to the group activity patterns, e.g. missing or reducing of the standing peaks related to feeding, a reduced height of peaks of the last peaks, etc. Moreover, individual variations should also be considered when identifying the individual activity patterns deviating from the group activity patterns. The individual patterns in a calf could be related to many factors other than sickness, e.g. the dominance hierarchy and the related replacements at the feed bunk (Foris *et al.*, 2019), calves' personality, etc. Further study should look into the range of individual variations of the normal activity patterns.

In this study, we applied a two-categorical activity variable to fit the model. A three-categorical activity variable distinguishing standing, walking, and lying time, could represent more detailed activity patterns of a healthy calf. Further studies should look for a predictive model that can fit such categories. In addition, as explained in the Material & Methods, we did not include discreet variables (i.e. step counts, number of lying bouts) in the analysis among the five recorded variables of the activity dataset. Step counts (Pillen *et al.*, 2016) and number of lying bouts (Swartz *et al.*, 2020), however, were reported to be important indicators for detecting sickness in a calf. Further study should look for models fitting the discreet variables (i.e. step counts, number of lying bouts) from the current dataset, e.g. 0-inflated possion model. Moreover, we obtained the feeding dataset from the AMFs, including individual feeding time, time visiting the AMFs, and milk replacer intake of each visit. This information might be useful for further developing a disease detection model, combining with the abnormal activity pattern detection. Similar suggestions were also given by recent studies (Bowen *et al.*, 2021; Conboy *et al.*, 2021; Lowe *et al.*, 2021; Cantor and Costa, 2022).

3.5 Conclusion

We conclude that the activity pattern of healthy group-housed calves, corrected for trends over time, can be described by a binomial logistic model of the pattern changes over weeks, with a moderate predictive performance. Interesting features to extract from such activity patterns include the number and timing of peaks, as well as the proportion of night-time activity. These features, and more specifically, meaningful deviations from the average levels of these features may correspond to health or welfare issues in calves.

3.6 Tables

Table 1 Average milk replacer intake in healthy calves (±XX; SD)

Week of age	Milk replacer intake (mL)
8	6529 ± 826
9	6580 ± 875
10	6453 ± 886
11	6762 ± 900
12	6969 ± 887
13	7241 ± 933
14	7490 ± 869
15	7570 ± 929
16	7703 ± 1036
17	7841 ± 1018
18	8058 ± 1068
19	8346 ± 1096
20	8845 ± 1215
21	9526 ± 1168
22	10283 ± 1268
23	11117 ± 1345
24	11943 ± 1449
25	12675 ± 1770

Table 2 Calf health score

	Calf health scorer			
Score	0	1	2	3
Temperature (°C)	37.8-39.4	>39.4		
Navel infection	Normal	Enlarged, not warm or painful	Enlarged, with pain, heat or moisture	
Prepuce/urine sucking	Normal	Moisture, enlarged, not warm, without pain	Moisture, swollen, warm	
Attitude	Normal, bright, alert, responsive	Dull but responds to stimulation	Depressed, slow to stand or reluctant to lie down	Unresponsive to stimulation
Behind in weight and condition	Normal	15-30%	>30%	
Bloat	Normal	One side	Two sides	
Abnormal breathing	Normal	>40/min		
Cough	No cough	Single cough occurrence	Repeated or occasional spontaneous coughs	Repeated spontaneous coughs
Diarrhoea (calf number)	Normal	Faecal score = 2 or 3		
Nose	Normal	Small amount of unilateral cloudy discharge	Bilateral cloudy or excessive mucus discharge	Copious bilateral mucopurulent discharge
Eye	Normal	Small amount of ocular discharge	Moderate amount of bilateral discharge	Heavy ocular discharge
Ear	Normal	Ear flick or head shake	Slight unilateral droop	Head tilt of bilateral droop
Joint, lameness, bursa problems (note down front or hind legs)	Normal	Slight swelling, not warm or painful	Swelling with pain or heat	
Skin damage	Normal	Single source of damage	Multiple sources of damages	
Faecal (at pen level)	Normal	Semi-formed, pasty	Loose, but stays on top of bedding	Watery, sifts through bedding

To check calf condition, compare our experimental calves with the rest of the stable (and not just the other calves within the same pen);

Total score besides temperature and diarrhoea: 4 (watch), 5 or more (treat), faecal score: 2 or 3 (treat), temperature/diarrhoea=1 (treat)

Temperature: write down the actual temperature

Table 3 Average activity of being active and being inactive in healthy calves

Weeks of age	Active (%)	Inactive (%)
8	31.5	68.5
9	32.5	67.5
10	32.1	67.9
11	32.9	67.1
12	34.1	65.9
13	33.1	66.9
14	33.4	66.6
15	33.3	66.7
16	33.5	66.5
17	33.9	66.1
18	35.8	64.2
19	35.2	64.8
20	35.7	64.3
21	36.4	63.6
22	36.2	63.8
23	36.3	63.7
24	37.0	63.0
25	37.0	63.0

Table 4 Extracted features of the smooth curves of active activity patterns in healthy calves

Week of age	Number of peaks	Proportion of night activity	Time of peak (1st)	Time of peak (2nd)	Time of peak (3rd)	Time of peak (4th)	Height of peak (1st)	Height of peak (2nd)	Height of peak (3rd)	Height of peak (4th)
8	4	0.20	4:48	10:33	16:05	21:07	0.15	1.20	1.06	1.69
9	4	0.21	5:17	10:33	16:05	21:21	0.20	1.49	1.11	2.08
10	4	0.21	5:17	10:33	16:19	21:21	0.30	1.56	1.17	1.85
11	4	0.22	5:17	10:48	16:05	21:21	0.47	1.54	1.11	1.94
12	4	0.21	5:17	10:48	16:05	21:21	0.48	1.69	1.25	1.95
13	4	0.21	5:17	10:48	16:19	21:21	0.63	1.69	1.22	1.69
14	4	0.20	5:31	10:48	16:19	21:21	0.50	1.70	0.80	1.59
15	4	0.21	5:17	10:48	16:19	21:21	0.66	1.80	0.97	1.55
16	4	0.20	5:17	10:48	16:19	21:21	0.68	1.81	0.98	1.53
17	4	0.18	5:17	10:48	16:33	21:07	0.85	1.93	1.08	1.37
18	4	0.20	5:31	10:48	16:19	21:21	0.74	2.07	1.03	1.81
19	4	0.21	5:31	10:48	16:19	21:21	0.87	2.03	0.85	1.56
20	4	0.21	5:31	10:48	16:19	21:21	0.80	1.90	0.88	1.59
21	3	0.21	5:31	11:02	21:07	NA	0.18	1.31	1.25	NA
22	3	0.24	5:31	11:31	21:21	NA	0.13	1.24	1.38	NA
23	3	0.26	5:31	11:45	21:36	NA	0.24	1.02	1.48	NA
24	3	0.26	5:46	12:29	21:36	NA	0.23	1.02	1.39	NA
25	3	0.27	5:46	12:29	21:36	NA	0.06	1.06	1.60	NA

Appendix 1 Weekly average summary of daily activity in healthy calves

Weeks of age	Standing time (%)	Lying time (%)	Walking time (%)	Number of steps	Number of lying bouts
8	27.6	68.5	3.9	5040	19
9	28.9	67.5	3.6	4754	18
10	28.5	67.9	3.6	4775	19
11	29.3	67.1	3.6	4780	18
12	30.0	65.9	4.1	5311	20
13	29.3	66.9	3.8	5047	20
14	29.5	66.6	3.9	5186	19
15	29.3	66.7	4.0	5230	19
16	29.4	66.5	4.1	5374	20
17	29.9	66.1	4.0	5261	20
18	31.4	64.2	4.4	5719	20
19	31.0	64.8	4.2	5566	21
20	31.2	64.3	4.5	5841	21
21	31.6	63.6	4.8	6120	21
22	31.4	63.8	4.8	6168	21
23	31.6	63.7	4.7	6051	22
24	32.3	63.0	4.7	6065	21
25	32.4	63.0	4.6	6000	21

Chapter 4 Computer vision-based body weight estimation in group-housed calves

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Abstract

Body weight (**BW**) is a robust indicator of growth performance and health for calves. A regular BW measurement could support the identification of deviations from an estimated growth curve, allowing for timely adjustments in feeding and assistance in health monitoring. Recent studies suggest that image analysis and machine learning can be applied to 3D images for BW estimation. This study aimed at exploring computer vision and machine learning to accurately estimate BW using features related to body size obtained from top-view images of calves. Holstein and crossbred veal calves (n = 228; 17 ± 4 d of age at arrival) were housed in six large pens, each with an automated milk feeder and a RGBD camera. Scale-based BW was used as ground truth (**GT**), each calf was measured three times throughout the 6-month fattening period. The images were obtained when calves visited the automated milk feeders (**AMFs**). First, a deep learning object detection method MaskRCNN was trained for detecting the calves in the images, which was found to have an accuracy of 90%. Six-hundred-and-thirty-one images from 20 calves (35 ± 5 images per calf) containing the specific calves whose BW were measured, were selected by visual inspection. Using the images corresponding to a BW measurement, machine learning methods for predicting the BW were developed. One approach used features extracted from the pixel mask corresponding to the calf being weighed, to train the four BW models: linear regression (**LR**), support vector machine (**SVM**), random forest (**RF**), and extreme gradient boost (**XGB**). The other approach used a convolutional neural network (**CNN**) applied on the calf pixel instances with the measured weight as the target. Among the trained models, LR obtained the best result using features extracted from the RGB-mask and corresponding depth images with a median relative error of 0.05. However, this method is linear which may give errors for a longer period of estimation. LR and XGB are suitable models when BW needs to be extrapolated beyond the GT BW. For data with a non-linear correlation, RF, SVR and XBG obtained similar accuracy. However, smooth growth curves in individual calves have not yet been feasible especially for predicting previously unseen ranges of BW. Further work is required to improve the performance of the models, e.g. to improve the test set-up, to increase the number of images in the model training, and to ease the process of aligning suitable images.

Keywords: growth curve, machine learning, veal calf, weight gain, 3D image

4.1 Introduction

Body weight (**BW**) is a robust and direct indicator of growth performance and health for livestock (Maltz *et al.*, 1997; Segerkvist *et al.*, 2020). For meat-producing farms, the economic performance is directly linked to BW: low BW (gain) often means lower feed efficiency, health issues and costly treatments, and lower carcass weight at the slaughterhouse, thus lower profit. In veal sector, for example, diseases in calves such as bovine respiratory diseases and diarrhoea have an negative impact on hot carcass weight in slaughter (Pardon *et al.*, 2013), and a higher arrival weight of calves is associated with a higher daily weight gain (Renaud *et al.*, 2018c). Therefore, a regular BW measurement of the calves assist a better management procedure. In the veal sector, however, BW measurement is not done systematically: BW of calves on arrival is usually not recorded, live BW is not measured during the fattening period, only carcass weights are measured at the slaughterhouse.

The most accurate way of BW measurement is using scales. However, traditional scale-based measurement makes regular BW measurement a difficult task due to the noisy character of the data. For example, eating, drinking or urinating or defecating will change weight rapidly and requires some data filtering to monitor significant weight changes. In addition, this requires much time and labour, and likely causes stress to the animals. Alternatively, measuring body dimensions e.g. body length, hip length, and withers height can give approximate BW because of its high correlation to BW (Dohmen *et al.*, 2021). If done manually, once again this requires intensive labour, time and animal handling and can be dangerous for the farm staff when animals grow larger, thus not feasible for frequent measuring of individual calves in a large group.

Recently, different approaches have been explored for automatic BW measuring in cattle rearing. Automatic scale-based systems have been developed for different rearing systems, e.g. walk over weigh system designed for extensive beef cattle systems (e.g. Tru-Test Flexi Mobile 4000c, Datamars Inc., US), or forefront weight scales designed to attach to an AMF for dairy and dairy-beef calves (e.g. electronic half-body animal scale, Förster-Technik, Germany) and Sharpe and Heins, 2023). However, the direct BW measuring devices have the same disadvantages as the conventional scales such as requiring repeated calibration and maintenance and are therefore less appealing to small and medium size farms (Wang *et al.*, 2021). An alternative approach which is both labour free and non-invasive is using 3D video cameras, to combine computer vision and machine learning techniques in the estimation of BW (Wang *et al.*, 2022). Despite the advantages of such an approach, the application of deep learning algorithms in BW estimation is still very limited (Dohmen *et al.*, 2021). This method does not require much investment, allows for multiple images to be taken to develop an algorithm for body size or volume estimation, and subsequent BW estimation. Besides, remote monitoring allows animals to walk freely, and avoid the stress caused by the presence and handling of humans. In pigs, for example, BW can be estimated with images applying a neural network (Cang *et al.*, 2019) or a YOLO-based algorithm (Franchi *et al.*, 2023). To date, however, we have not found a study estimating BW based on deep learning using 3D images in calves housed in large groups.

In this study, we applied the most widely used models used for machine learning, including Linear Regression (**LR**), Support Vector Machine (**SVM**), Random Forest (**RF**), Extreme Gradient Boost (**XGB**), and a convolutional neural network (**CNN**) regressor for the BW estimation. The objectives of this study were, 1) to train different models that estimate BW using body sizes extracted from 3D images, and 2) to evaluate the performance of these models. We expected that at least some of these models could accurately estimate the BW in veal calves based on the images obtained from 3D cameras.

4.2 Materials and methods

This study was performed on a commercial veal fattening farm in the Netherlands between July 2021 and January 2022. The study was approved by the Central Committee Animal Experiments (Centrale Commissie Dierproeven, CCD; beschikking 2655) in the Netherlands. This study is part of a larger project which applied multiple automated tools (including accelerometers, automated milk feeders (**AMFs**), and 3D cameras). In this study, only 3D camera related results were reported.

4.2.1 Animals, housing, and management

Two-hundred-and-twenty-eight Holstein and crossbred veal calves (17 ± 4 d of age at arrival, mean ± SD) were included in the study. Registration information of the calves was obtained from the farm. Both sexes were included (male N=202, female N=26). Calves were kept individually in so-called ‘babyboxes’ inside the group pens for the first four weeks following arrival and were thereafter released into six large pens (N=38 ± 2 calves per pen, mean ± SD). During group housing, calves were fed milk replacer through an AMF (N=6, Förster-Technik

GmbH, Engen, Germany). Water was supplied 6 h per day in two periods (from 8h00 to 11h00, from 20h00 to 23h00) through an automatic water drinker. Calves had ad libitum access to starter through one shared trough per group. The calf starter consisted of a mixture of chopped straw and concentrates. The roughage contents changed over time and were mixed with approximately 15% finely chopped straw. Concentrate contents were gradually mixed on overlapping days (roughage concentrate contents: day 1 to 35 on arrival - protein:12.5%, fat: 4.5%, crude fibre: 7.7%. Day 14 to 80 on arrival - protein: 17.0%, fat: 4.0%, crude fibre: 5.3%. Day 70 onwards on arrival - protein: 14.0%, fat: 4.0%, crude fibre: 5.3%).

Each pen in the group housing was equipped with enrichment in the form of several rubber teats (per pen: ± 6 teats mounted on the wall and ± 6 teats in a bucket hanging from the ceiling), one scrubbing brush, one mineral block and one large yellow skippy ball hanging from the ceiling. Pens were equipped with rubber coated slatted flooring. Artificial lighting was on only when farm staff was present (around feeding times: 8h00, 16h30; daily inspection), and the barn was most often lit by natural light through windows. The ventilation system in the barn comprised of ventilators and side curtains.

4.2.2 Body weight data

Scaled-based BW of individual calves were recorded three times during the fattening period (weighing scale: ISC-V, Henk Maas Scales, the Netherlands; e = 0.1kg, max = 300 kg, min = 2 kg) starting at 10, 14, 19 weeks after arrival. For the practicality of the work, BW measurement was carried out after the clinical examination day (twice per week, for 16 consecutive weeks. Data of clinical examination was used and reported elsewhere), two pens of calves were measured each time prior to their afternoon feeding session. A total of 650 BW measurements from 228 calves was obtained (missing data were due to 1) the difficulty of handling the calves, 2) calves' sizes were too big to go through the gate of the weighing scale, 3) calves were absent in the pen on the measuring date).

4.2.3 Imaging protocol

Depth cameras (Intel® RealSense™ Depth Camera D435, Intel Corporation, Santa Clara, California) were placed directly above the AMF, at a height of 1975 mm above floor level, and a horizontal distance of 825 mm to the teat of the AMF (Fig. 1). Active Infra-red stereo technology was used for depth measuring. The depth cameras recorded output in 720p at 3μm×3μm pixel size. Open-source software Intel® RealSense™ SDK 2.0 was provided for automatic calibration (Intel®, 2021). RGB and depth images were taken when calves visit AMFs and were stored on the server.

Fig. 1 The allocation of depth cameras above the automated milk feeders

4.2.4 Data management

All data processing was written in Python 3.8 (van Rossum and Drake, 2009). A flow chart (Fig. 2) was drawn to present how the data was processed.

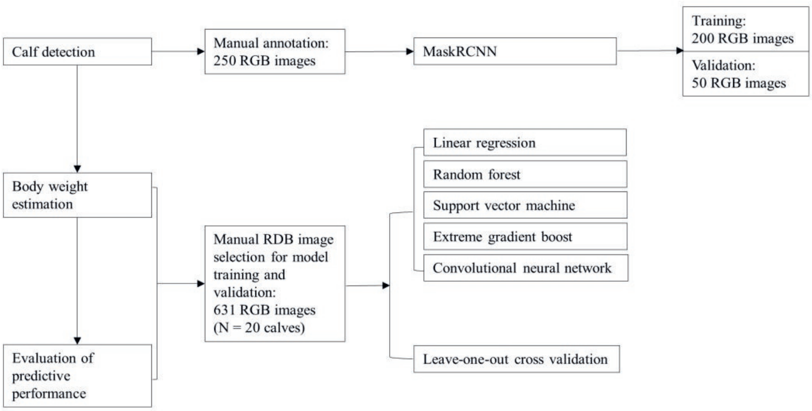

Fig. 2 Flow chart of data processing

4.2.5 Calf detection using MaskRCNN

Two-hundred-and-fifty RGB images were used. To identify the individual calves from the RGB images, the time of the images being taken were manually matched to the same time a calf visiting the AMF (calves were identified at the AMF through their RFID ear tags. Feeding information including time visiting the AMF, feeding time, and milk replacer intake of individual calves were recorded by the AMF and stored automatically on the computer at the farm). Calf registration information (e.g. with fur colour recorded) was used for a manual double check if the calves were rightly identified. The 250 RGB images were annotated using image polygonal annotation tool labelme (Kentaro, 2016. https://github.com/wkentaro/labelme). The contour of the calf in the image were manually drawn using a sequence of points forming a polygon (Fig. 3). The enclosed area within the polygon is called the mask and it is the region-of-interest (**ROI**) for further processing to estimate the BW. An example of an annotated image with the calf pixel mask overlaid is shown in Fig. 4.

Fig. 3 An example of drawing the contour of a calf manually

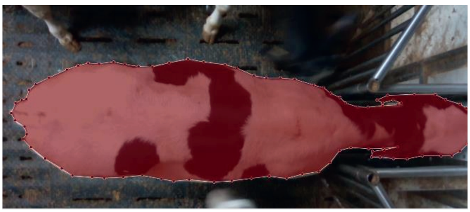

Fig. 4 An example of an annotated image with the calf pixel mask overlaid

A subset of the annotated RGB images (N=200) were used to train the deep learning model MaskRCNN (He *et al.*, 2017) implemented in Detectron2 (Wu *et al.*, 2019. https://github.com/facebookresearch/detectron2) for calf detection (Fig. 5), and 50 RGB images were used for validation. MaskRCNN is an object instance detector and outputs a mask of the pixels corresponding to the calf visiting the AMF in each RGB image. The ROIs obtained by the RGB image were applied on the corresponding depth data obtained by the depth-camera to provide several features, including the total number of pixels in the mask, the minimum, maximum, mean, and median values of the depth data.

Fig. 5 An example of an annotated RGB image

4.2.6 Body weight estimation models

To train machine learning methods to estimate the BW of a calf from an image, a set of images with the respective BW at the time of the image acquisition is required. Thus, for a particular calf which was weighed, a corresponding image on or close to the day of weighing needs to be located. This is not a trivial task because there are often more than one calf in the images, necessitating manual inspection and selection of the images. Following this protocol, twenty male calves were identified as being clearly visible without occlusions at the AMF top-view images taken on or close to the days of their respective weightings. Moreover, to obtain the individual growth curves for these animals, their subsequent images other than the dates of measurement were also selected manually. Those RGB images were selected with 1) a single calf in the image, 2) a complete calf in the image, and 3) with a 3-day gap in between images. Images from one day prior (or after) were selected when no suitable images can be found on the original selected days. This resulted in a total of 631 images being selected (approximately 35 ± 5 images per calf), out of which 55 images had a corresponding ground truth, i.e. scale-based BW measurement (2 or 3 images per calf).

Four machine learning models: LR (Linear Regression), SVM (Support Vector Machine), RF (Random Forest), XGB (Extreme Gradient Boost) were applied to train the BW estimation models using the features obtained from the data frames. A CNN (convolutional neural network) regressor was also trained to predict the BW directly from an input image. Out of the methods that work with the features, LR (James *et al.*, 2017) is the simplest and involves a linearly weighted sum of the features. Denoting the weight of the i^{th} calf as y_i and the feature vector as x_i, the relation is formulated as

$y_i = \Sigma\, x_{i,j}\, w_j + w_0$

The vector of regression coefficients **w** is estimated from the training data by solving the least squares problem

$\arg\min_w \Sigma\, (x_{i,j}\, w_j + w_0 - y_i)^2$

This approach has the restriction that it may be insufficient to model behaviour that deviates from a linear relationship. Support Vector Regression (**SVR**) (Drucker *et al.*, 1996) overcomes this problem by using a kernel function φ such as the radial basis function to be able to model non-linearities. The idea of SVR is to fit the error inside a certain threshold which amounts to approximating the best value within a given margin, minimize

$w^T w$ subject to $|y_i - w^T \varphi(x_i) - w_0| \leq \varepsilon$

Another supervised learning method which can be used for classification as well as regression is the RF (James *et al.*, 2017). It uses ensemble learning in that it combines predictions from multiple decision trees to obtain a more accurate prediction than an individual tree. RF is trained by iteratively building decision trees based on randomly selected data points and predicts a value on a new data point by averaging across the predicted values over all the trees. RF can model non-linearities but has a drawback in that it needs to be trained with expected values thus it may be inaccurate while predicting previously unseen ranges of values.

XGB (Chen *et al.*, 2015) uses gradient boosting on the decision tree algorithm for regression or classification. In this approach, new models are created that predict the residuals or errors of existing models and are then added together to contribute to the final prediction. A gradient descent algorithm such as Newton-Raphson is used to minimize the loss function when adding new models.

Finally, CNN for regression consists of a deep neural network without a final non-linear layer, which is typically used for classification (Goodfellow *et al.*, 2016). This approach uses the RGB and depth images as inputs to the network, along with the age in days (calculated as the difference between the date of the image and the respective calf's date of birth) encoded as a constant matrix. The input is thus a five-channel tensor, which is resized to 128 times 128 pixels. The architecture used is shown in Fig. 6. The first few layers called the convolutional layers apply filters and pooling on the tensor and at the end produce a vector of length 512. This part of the architecture was previously used for estimating the biomass of lettuce plants

(Zhang *et al.*, 2020). The next part, called the fully connected layers, have connections between all nodes across two consecutive layers. The final layer outputs a scalar value, i.e. the predicted weight. While the CNN approach does not need to explicitly define the features from which to learn the weight, it requires many more data points and consequently, annotation effort and cost. Moreover, it is not straight-forward to incorporate additional information.

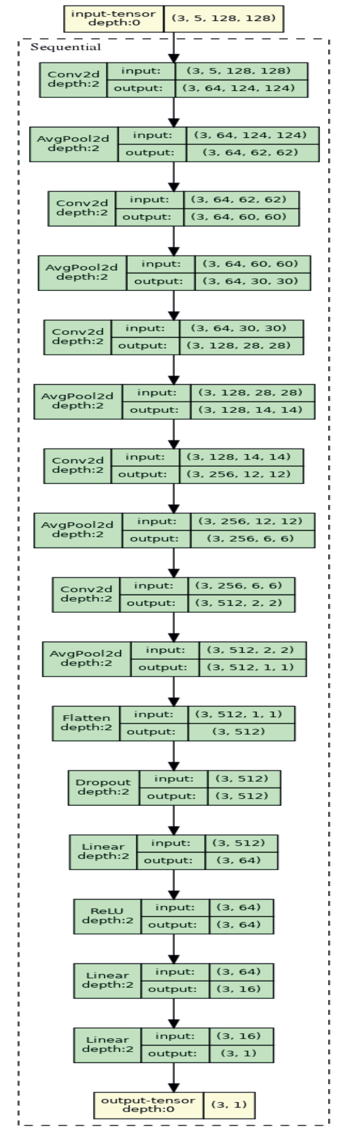

Fig. 6 The architecture of the Convolutional Neural Network

4.2.7 Evaluation of predictive performance

Leave-one-out cross validation was carried out to evaluate the performance of the five models described above. Each model was trained by leaving one animal out and training on all other animals. The absolute error and proportional error for the predicted BW were estimated compared to the ground truth.

4.3 Results

4.3.1 Ground truth data

Six-hundred-and-fifty individual scaled-based BW measurements from 228 calves were obtained, 25 measurements failed due to the difficulty of handling the calves (N=23) or the calves were too big to walk into the scale (N=2). Descriptive statistics of scale-based BW measurement are presented in Fig. 7: calves had mean BW of 93 ± 8.7 kg (at 79 ± 6.5 days of age), 133.4 ± 10.7 kg (at 113 ± 6.1 days of age), and 179.4 ± 14.4 kg (at 145 ± 4.6 days of age).

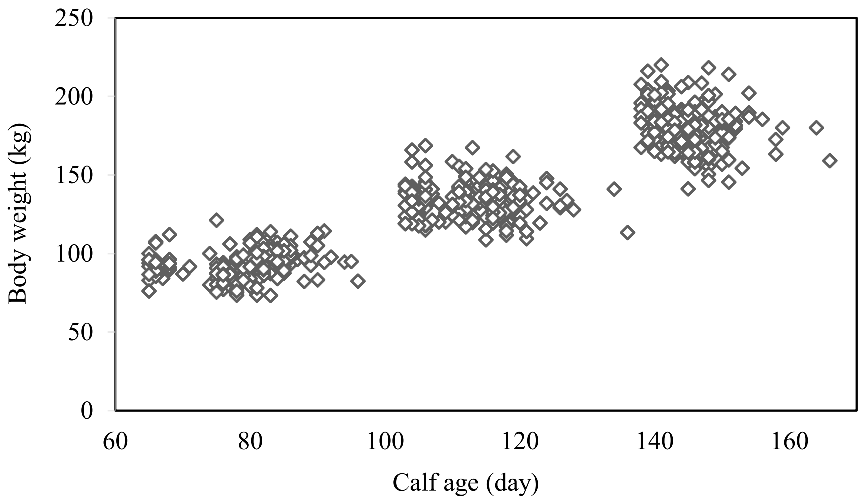

Fig. 7 Scattered plot of scale-based body weight measurement

4.3.2 Validation of calf detection

For the calf instance segmentation using maskRCNN, a precision of 93% was obtained (i.e. 93% of detected calves were valid) on the validation set, with a recall of 100%: all valid annotated calves being detected (i.e. no false negatives). The Jaccard index or intersection over union (**IOU**) which indicates the degree of overlap between the annotated ground truth pixel masks and the detected ones was found to be 94%.

4.3.3 Predictive performance of supervised machine learning models

The predicted BW obtained using the five models are presented in Fig. 8. For each selected calf, 3 estimated BW were plotted in comparison to the corresponding GT (i.e. scale-based BW measurement) of the same approximate dates.

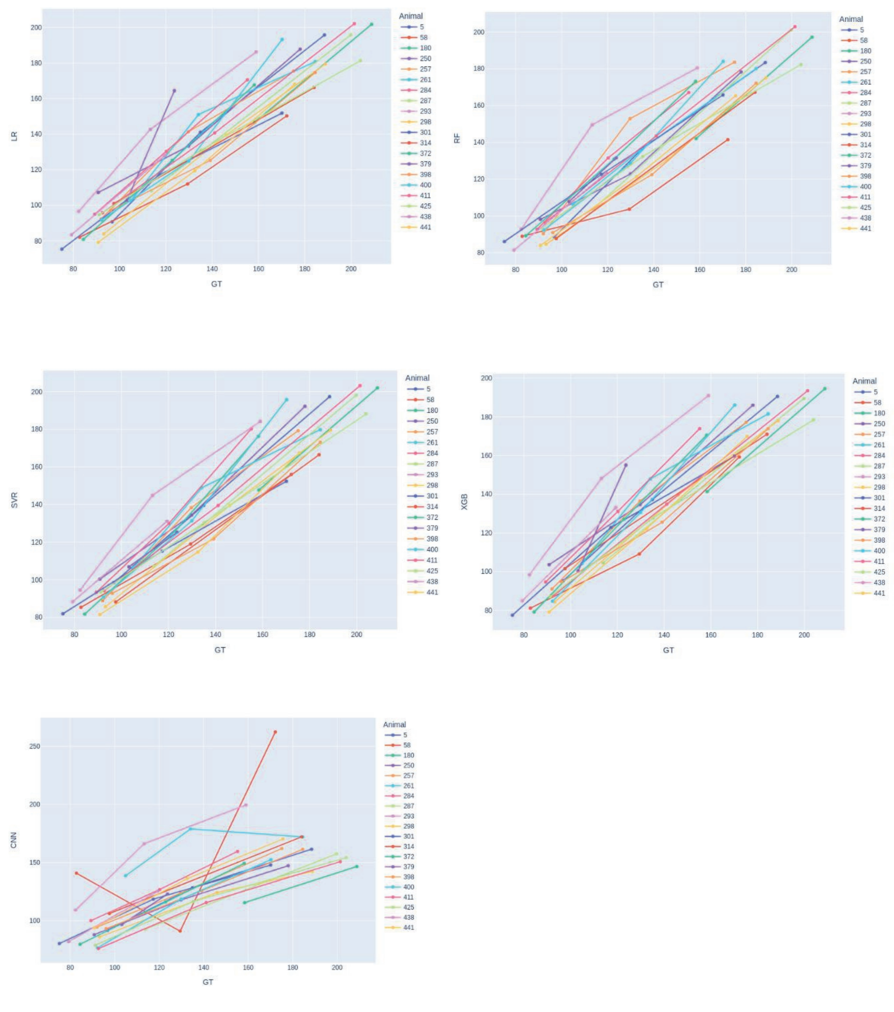

Fig. 8 Predicted body weights of the tested models

4.3.4 Leave-one-out cross validation

Boxplots of absolute error and relative error of the five models are presented in Fig. 9. The metrics of leave-one-out cross validation are shown in Table 1 (absolute errors) and Table 2 (relative errors). CNN obtained a much higher median absolute error and median relative error and was therefore dropped and not included in the below comparison. Among the other four trained models, in terms of absolute errors, LR had the lowest median absolute error yet had the widest spread of absolute errors; SVR had the smallest spread of absolute errors although not the smallest median absolute error; RF and XGB had the largest median absolute errors but had smaller spread of absolute errors than LR. In terms of relative errors, SVR and LR had the lowest median relative errors, but SVR had the lowest spread of relative errors while LR had the largest spread of relative errors; RF had the highest median relative error with a medium spread of relative error; XGB had a higher median relative error than SVR and LR, with the spread of relative errors larger than SVR yet smaller than LR.

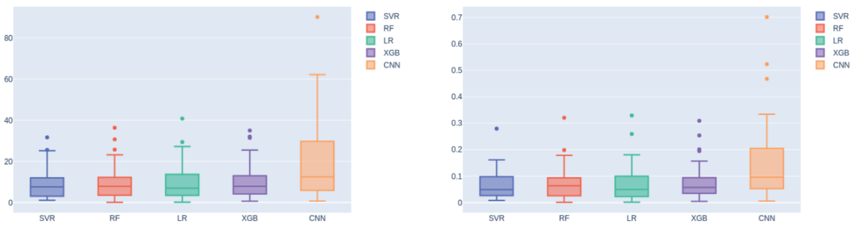

Fig. 9 Predictive performance of the tested models[1]

[1]Left: absolute errors; right: relative errors.

4.3.5 Growth curves of the models

Growth curves estimated from the five models are presented in Fig. 10. To have a smoother growth curve, we added a two-neighbourhood median filter to the estimated growth curve: each BW point in a curve is based on the median of the two points prior to and after. Growth curves estimated from the models with a weight average filter are presented in Fig. 11, less outliers were generated compared to the growth curves of the raw data. As shown in Fig. 11, the estimated BW of the tested models showed relatively smooth increases (when GT BW data were available) before large fluctuations (when GT BW data were not available) except CNN (not included in the discussion because of the high errors). All four models had huge outliers when no GT BW measurements were available. Within the range of available GT BW measurements, LR and XGB showed smoother growth curves than SVR and RF.

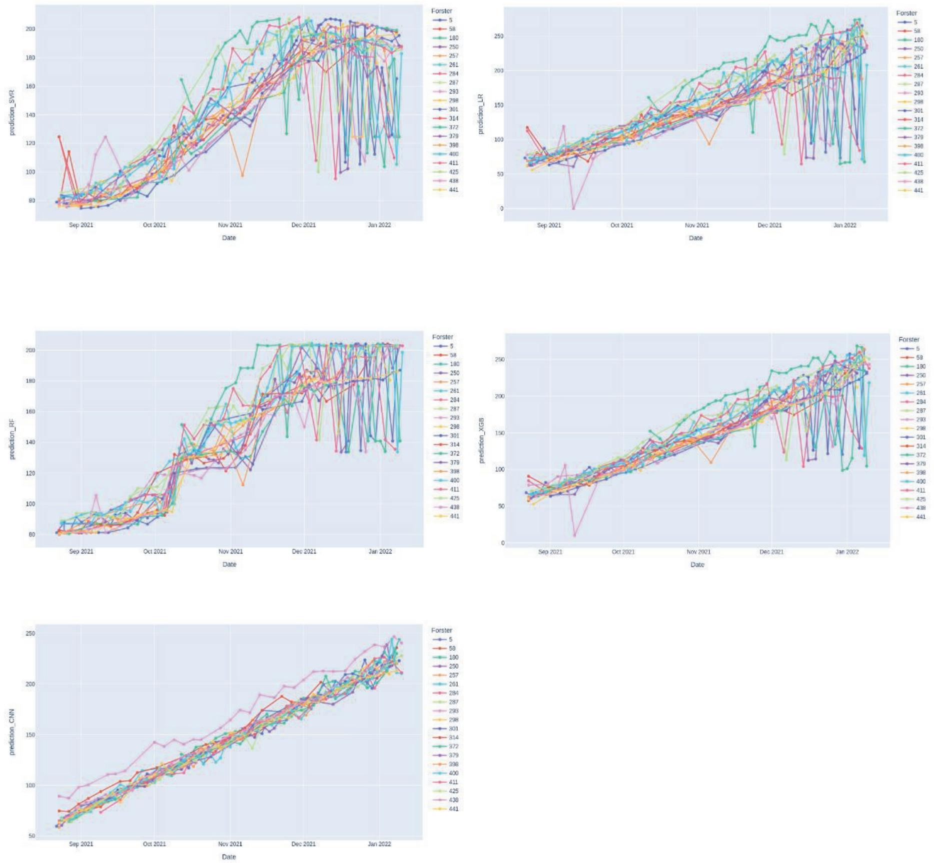

Fig. 10 Estimated growth curves of the tested models

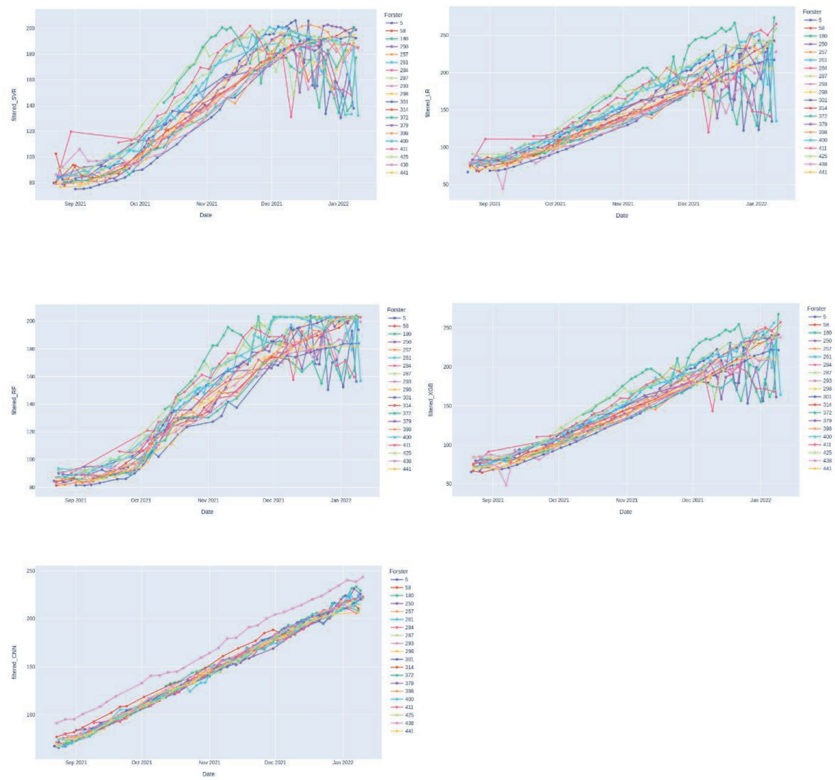

Fig. 11 Estimated growth curves of the tested models adding weight average filter

4.4 Discussion

The aim of the study was to test the performance of four supervised machine learning models and a CNN for regression in estimating the BW of group-housed calves, based on the 3D images taken above the AMFs. The tested models, except CNN, showed good predictive performance. Among the remaining four models, SVR and LR obtained the best performance in BW estimation in terms of absolute errors and relative errors. In terms of the estimated growth curves, however, XGB and LR showed smoother curves than RF and SVR.

To evaluate the predictive performance of trained models, we applied the metrics absolute error, i.e. the absolute difference between the scale-based BW and the predicted BW from an image, and the relative error, i.e. the absolute error divided by the GT. LR is known as a benchmark performance to comparing with machine learning methods (Dohmen *et al.*, 2021). In our study, LR obtained better performance (lower relative error) than RF and XGB but less as good as SVR. This result is different from Gebreyesus *et al.* (2023) reporting that tree-based group of supervised learning techniques (Catboost, AdaBoost, RF) resulted in the highest prediction performance in all the metrics used to evaluate technique performance (i.e. LR, tree-based regression, SVR).

Among the four models, XGB and LR generated the smoothest growth curves, while XGB obtained less outliers compared to LR. SVR and RF had the most unstable growth curves: the estimated growth curves from SVR and RF seem to be smooth in the beginning of the time series, with errors and uncertainty building up over time. The predictions obtained with RF seem to plateau out or increase very slowly after the dates for which measurements were available. While this is not unexpected as RF needs to be trained with possible anticipated values, the resulting growth curves are chosen to an S shape. In terms of SVR, although obtaining the best predictive performance in estimating BW, the fluctuated curve from SVR indicated that it may not be stable for fitting the current dataset.

In addition, although the CNN regressor performed the worst of the methods in both the cross validation as well as the almost linear final growth curve, it must be noted that deep learning typically needs many more data points than other methods. Nevertheless, the results obtained show the application of the complete pipeline, which can be expected to improve in future with additional data.

In this study, we only obtained three scale-based BW measurements for each calf over the time-range of three months. Unfortunately, we dropped the fourth BW measurements because the calves were too big to handle and to walk through the scale. The lack of higher body weights resulted in the poor performance of the growth curves at older age (i.e. outside the range of the GT BW measurements). In the current study, we carried out a monthly scale-based BW measurement, which is fine for a "proof of principle". A more frequent BW measurement is required for the training of the models. In a commercial farm setting-up, however, this would cause additional stress moments to the calves therefore may not be favoured. A built-in automated BW scale incorporated into the AMFs, e.g. automatic calf weighing scale from Forster-technik (Automatic calf scale for the automatic feeder| Förster-Technik (foerster-technik.com)), might be useful to obtain a larger reference dataset and not stress the calves. A comparison of the accuracy of these two methods (i.e. between automatic weighing scale and 3D cameras) might be interesting for further study. Furthermore, we also suggest a higher number of images be included for further training the models.

MaskRCNN was used for background subtraction, allowing for manually selecting suitable images for annotation. The mask had a high precision, suggesting that maskRCNN is a reliable model for calf detection in a farm environment. The manual annotation, however, is time-consuming, which limited our inclusion of more images for training maskRCNN model. A more efficient way of annotating (preferably automatic) should be explored. An alternative way is to apply deep learning techniques to detect calves directly without the need to annotate, e.g. 3D Time of flight (Dohmen *et al.*, 2021). In addition, data preparation is crucial (Dohmen *et al.*, 2021). In our study, many recorded images had calves in a position in which they bended lateral, for example to look aside or behind them. Such curved back might affect the generated mask of the MaskRCNN, further affect the model training and validation. To avoid bended positions, it is suggested to add barriers at the AMFs to allow calves stay straight when drinking milk. This also will reduce the fighting and the frequent calf replacements at the AMFs, allowing cameras to take more images of the same calves in similar positions, which benefits the later image selection process. Other images that are too dark or unclear, with more than one calf, occlusions, with incomplete calf image, should also not be included for the data processing.

4.5 Conclusion

3D images, subsequent features in combination with machine learning models, are able to predict the BW of calves with high accuracy. Among the trained models, LR obtained the best result using features extracted from the RGB-mask and corresponding depth images with a median relative error of 0.05. However, this method is linear which may give errors for a longer period of estimation. LR and XGB are suitable models when BW needs to be extrapolated beyond the GT BW. For data with a non-linear correlation, RF, SVR and XBG obtained similar accuracy. However, smooth growth curves in individual calves have not yet been feasible especially for predicting previously unseen ranges of BW. Further work is required to improve the performance of the models, e.g. to improve the test set-up, to increase images in the model training, and to ease the process of aligning suitable images.

4.6 Tables

Table 1 Absolute errors of leave-one-out cross validation

Method	Absolute error (median, kg)	Absolute error (maximum, kg)	Absolute error (minimum, kg)	Absolute error (spread, kg)
Support vector regression	7.6	31.7	1.1	30.6
Random forest	7.9	36.3	0.1	36.2
Linear regression	7.0	40.8	0.2	40.6
Extreme gradient boost	7.9	35.0	0.6	34.4
Convolutional neural network	12.4	90.1	0.7	89.4

Table 2 Relative errors of leave-one-out cross validation

Method	Relative error (median)	Relative error (maximum)	Relative error (minimum)	Relative error (spread)
Support vector regression	0.049	0.280	0.008	0.272
Random forest	0.064	0.321	0.001	0.320
Linear regression	0.050	0.330	0.002	0.328
Extreme gradient boost	0.058	0.309	0.005	0.304
Convolutional neural network	0.096	0.702	0.006	0.696

Chapter 5 General discussion: the not yet-included (but important) values in developing precision livestock farming

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In this chapter, I will first summarise and discuss the results of all previous chapters, and identify the potential applications of current results, how the current study can contribute to alleviate the concern of high antibiotic use in the veal sector and how this study may contribute to improving calf health and welfare. I will also briefly share the future plans linked to further analysis of the dataset presented in this thesis. In the second part, I will jump out of the current line of thought, and bring readers to think with me, using our study as an example, to reflect on the (subtle) misleading promises precision livestock farming (**PLF**) might bring, and invite readers to think of the possibilities of embracing a PLF approach with different priorities, i.e. a more animal-oriented approach.

5.1 Summary and applications of this thesis

5.1.1 Health and welfare risks in veal production, and the PLF approach as a potential solution

Following the conventional visual appraisal and clinical examinations at the fattening farm, sick calves are often identified at an advanced stage of disease or not at all (White *et al.*, 2009; Decaris *et al.*, 2022), leading to a more intense and wide spread of pathogens, and subsequent group treatments with antibiotics. For the farmers, sick(er) calves mean lower carcass weight at the slaughterhouse and costs for treatments, and consequently less profit (Lora *et al.*, 2022). The causes of the sickness, however, are complex and relate to many challenges veal calves face throughout the entire production cycle, e.g. at the source dairy farm (Renaud *et al.*, 2018b), during transportation (Marcato *et al.*, 2018), and at the fattening farm (Renaud *et al.*, 2018a). Identified risk factors include: a young transport age (Marcato *et al.*, 2022a; Marcato *et al.*, 2022b), high numbers of calves (and the contacts among them) and large age variation of calves in the same arrival batch (Sandelin *et al.*, 2022), mixing procedures, and a new housing environment (Marcato *et al.*, 2018). Multiple approaches were proposed to reduce the risk factors that cause the sickness, e.g. allowing sufficient early dam contact before transport (Haskell, 2020; Webb *et al.*, 2022), assuring an adequate body weight (**BW**) before transport (>50 kg), adequate transferring of passive immunity, specific immunity by vaccination (Renaud and Pardon, 2022), scoring dehydration and BW at arrival (Renaud *et al.*, 2018c), classifying calves according to disease risk on arrival (Renaud and Pardon, 2022), and applying real-time health monitoring tools, e.g. accelerometers (Puig *et al.*, 2022). In addition, standardized disease control programs were suggested to be developed and validated to allow a comparison across herd, regions or countries (van Roon *et al.*, 2019).

PLF use in health management is a complex matter, which requires careful investigative steps. Other bigger changes proposed include the combination of sexed semen and beef-breed crossing, to obtain more male beef cross calves at veal farms, which grow faster and may be more resilient, or to use dual-purpose breeds of cattle to integrate the dairy/veal and beef systems (Webb *et al.*, 2023).

In this thesis, we did not directly look at the use of PLF for health detection in calves, but rather, dived into stage two of our four-stage PLF framework: namely data interpretation. This thesis laid the foundations for early health monitoring in veal calves, aiming at reducing the potential over-appliance of antibiotics, especially the group treatments.

5.1.2 Summary of this thesis

In chapter two, we adapted a four-stage approach as proposed by Rutten *et al.* (2013) for developing PLF-based early disease detection tools in veal calves, i.e. 1) sensor technique, 2) data interpretation, 3) information integration, and 4) decision support. At stage one, automatic feeding stations, accelerometers, infrared thermography cameras, microphones, and 3D cameras are accurate in screening behaviour and physiology of calves. At stage two, changes in feeding behaviours, lying, activity, or body temperature corresponded to changes in health status, and point to health issues earlier than manual health checks. At stage three, accelerometers, thermometers, and automatic feeding stations have been integrated into one system which was shown to be able to successfully detect diseases in calves, including bovine respiratory diseases (**BRD**) and neonatal calf diarrhoea. Most studies up to now are at stage one (sensor technique) or stage two (data interpretation), a few studies are at the beginning of stage three (information integration). Clear gaps in research include stage three (information integration) and stage four (decision support) systems, as well as forecasting methods via the identification of low resilience animals. To develop a health detection model with a minimal number of sensors, it is crucial to select appropriate sensor systems, which can record the most relevant parameters that show clear changes in response to diseases in calves.

Based on our proposed framework and our results, this thesis falls in stage two - we reviewed the available sensor technology options available for monitoring calf behaviour and physiology (**Chapter 2**), described activity patterns of healthy calves using accelerometers (**Chapter 3**) and tested the efficacy of models applied to 3D images to predict calf body weight (**Chapter 4**).

Chapter 3 used generalized additive models (**GAMs**) to describe the group activity patterns in healthy calves and the changes of these patterns over time. The fitted model used the extracted features of the acceleration data to describe the activity pattern of 'being active' of group-housed calves during the fattening period, and we obtained a medium predictive performance. Though individual calves may show different activity patterns in a specific time window, the smooth curve of the group activity pattern over a long period of time is relatively stable. The smooth curve of the group can therefore be used as a valuable reference to compare to the activity pattern of an individual calf. However, the existing computing power limited the depth at which we could investigate the current dataset. Further work and time is needed to describe the activity patterns in a more detailed way, e.g. identifying lying, standing, and walking time, exploring different methods to analyse the current dataset is needed, looking at milk feeding data and looking more closely at individual patterns. Compared to recent studies on similar topics (e.g. Cantor and Costa, 2022; Ramezani Gardaloud *et al.*, 2022), our study differed on important aspects: it was based in a real commercial setting, with large numbers of animals, and the data were gathered over a long period of time (2 batches in 1 year). We further explored fitting the activity data of calves using GAMs, a model which was recently reported to fit data obtained from automated milk feeders for disease detection in pre-weaned dairy calves (Perttu *et al.*, 2023). Our results showed the ability of using GAMs to describe 'normal' group activity patterns in healthy calves, which can be used as the reference for further detection of the calves showing the 'abnormal' activity patterns, and further give early warnings to farmers.

Chapter 4 explored computer vision using machine learning techniques in estimating BW of calves from 3D images. Scale-based BW, taken at three time points during the fattening period, were used as the ground truth. A deep learning object detection method MaskRCNN was trained for detecting the calves in the images, which was found to have an accuracy of 90%. The extracted features from the images in combination with machine learning models, were able to predict the BW of calves with high accuracy (with median relative errors between 0.049 and 0.096). Among the trained models, linear regression obtained the best result using features extracted from the RGB-mask and corresponding depth images with a median relative error of 0.05. Based on the current BW estimation models, however, estimated growth curves in individual calves showed huge variations, especially for predicting previously unseen ranges of BW. Further work is required to improve the performance of the models, e.g. to improve the test set-up, to increase the number of images used for training, and to ease the process of aligning suitable images. The current result showed the feasibility of applying computer vision to 3D images for BW estimation and the potential to estimate the growth curves of individual calves. Further training of these models with a large number of images are needed for a smoother growth curve estimation.

5.1.3 Application of results in practice

The selected automated tools in our study (i.e. accelerometer for disease detection and 3D cameras for BW estimation) correspond to the two fundamental goals of the veal production in practice: achieve low mortality and good growth rates (Sandelin *et al.*, 2021). In **Chapter 3**, we showed the ability of using acceleration-based activity to describe the normal activity pattern of a group of calves, with the potential of detecting the activity pattens of individual calves deviating from the normal activity patterns. The identification of 'abnormal' calves will allow for a timely check of the individual calves and early treatment, reducing the chance of a sick calf infecting other calves in the same group, therefore lower the morbidity and consequently the mortality of the group. In **Chapter 4**, we showed the investigated computer vision using the combination of 3D images and machine learning models to predict BW of calves with high accuracy. The next step of this analysis - drawing the growth curves of individual calves with high accuracy - will allow for a continuous growth monitoring, which will instantly reflect the efficiency of the feeding and the management routine at the farm, allowing for relevant adjustment to reach the optimal growth rate. This growth curve could, as with activity patterns, further be used to detect deviations from normal which may point to disease.

5.1.4 Outlook and future work

Further data analysis is planned to reach stage three: 1) to study the individual variability of activity patterns, and the factors underlying the variability, 2) to explore an optimal model to detect individual calves that show deviations from the normal activity patten, 3) to develop the growth curve for individual calves, and 4) to explore how BW can be used to reflect the health status of a calf. This requires further exploring of different models using statistical tools. After these steps, data from different techniques need to be integrated into one model, this includes not only the activity data from accelerometers (chapter 3) and the images from the 3D cameras (chapter 4), but also the feeding information obtained from automated milk feeders (not included in this thesis). The most relevant variables in relation to disease occurrence (or deviations from normal patterns) can then be selected at this stage. In this next step, we need to search for appropriate models that can fit our large dataset, train and validate the models (an unused dataset consists of clinical examination scores, feeding information, and activity data is available). This approach is in line with suggestions from other studies, e.g. including field test and using previously validated reference tests to assess technology's performance for early BRD detection (Garrido *et al.*, 2023).

5.2 Will the current PLF approach solve the problem?

If the automated tools have been developed following the proposed approach, how much can the developed tools contribute to solve the original problem, i.e. lower morbidity and mortality and subsequently reducing antibiotic use in the practice of veal rearing? In our case, we applied PLF tools at the fattening farm, which eliminated the possibility of dealing with the risk factors at the source farms and during transportation, which to a large extent cause the disease occurrence at the fattening farm. The author acknowledges other studies that improve the health status and welfare condition of calves with a focus on other stages in the production, e.g. at the source farm or during transportation (introduced in 5.1.1). One fact, however, separates our PLF approach (i.e. at the fattening farm) with other aforementioned approaches (i.e. at the source farm or during transportation): detecting a sick calf earlier might indeed reduce the appliance of antibiotics (both in volume and type), but the early detection only allows a sick calf to be identified earlier, which does not change the fact that the calf still got sick in the first place, and still lives in the same conditions with the same risk factors for disease.

Putting the rationale behind the work in this thesis into question, the question is: should we focus our research efforts on detecting problematic issues in existing production systems, or on modifying these systems towards minimising risks or preventing issues arising in the first place? Modifying the current production systems, however, does not per se mean big changes for the commercial farms, unless the nature of the system itself is the main factor behind the issues that should be minimised. For example, to minimise lung infections, attaching sensors to calves might be less appropriate than improving the ventilation system in the house. However, preventive and risk reducing measures may require more and significant investments, e.g. reducing the stocking density, equipping better ventilation systems, or larger changes such as a re-design the farming system by incorporating animal capacities in engineering design (van Weeghel *et al.*, 2021), or applying a new rearing system such as an 'outdoor veal calf' system (Becker *et al.*, 2020). Even bigger system changes that reduce large causal factors to morbidity are envisaged, like including the lack of sufficient immunity transfer with milk from the dams, the transportation and mixing of young animals, and the low perceived value of these ‘surplus’ animals; this would be possible through the use of a combined dairy-beef farm using dual-purpose breeds of cattle (Webb *et al.*, 2023). This is not easy, as the current calf production sector has evolved over many years with deeply rooted practices of involved stakeholders in the production chain, e.g. farmers, supply industry, advisors, the veal industry, etc. If any of the above changes mean that one or more of the involved parties has to sacrifice its interests, who should and will pay the costs of these changes?

The discussion of balancing the interest of different groups is crucial but distracts us from focusing on the problem itself: to minimise morbidity in calves and reduce the use of antibiotics. Before reaching consensus (or compromises), different stakeholders at least should freely explore the uncompromised method to tackle the problem. Our proposed four-stage approach applies PLF tools at the fattening period, which presupposes that the veal production system as it now stands will not (have to) change, leaving small changes and additions to the current rearing systems the only option. If so, attaching sensors might indeed be a good solution, because it requires no further changes of the current indoor group housing systems, and requires no change of the transport system from current source farms to fattening farms. Following the proposed four-stage approach, development of PLF tools adds to the existing systems, but does not solve the inherent causes of the problems. In addition, the ‘calf’ is not considered as stakeholder in the decision-making process.

5.3 The ‘value hierarchies’ in PLF development

This brings the discussion to the potential societal and other risks of developing PLF. The author acknowledges different concerns regarding developing and deploying PLF, especially to the farmers, such as the concerns for adopting new technologies (Smith *et al.*, 2020; Stone, 2020), job loss and job simplification (Werkheiser, 2020), and underexamined issues such as the costs/benefit ratio of incorporating PLF tools to the farmers. This section, however, will not touch upon these concerns. Instead, the author would like to (try to) bring the readers to think of the impacts of developing PLF from a holistic point of view, using this thesis as an example. The most worrying concern, to the author’s mind, is the lack of ‘value hierarchies’ (Werkheiser, 2020).

To explain value hierarchies, we need to discuss the ‘related values’ that are taken into consideration when developing PLF. When developing PLF tools, besides the original problem these tools were developed for, they might also address other issues related to livestock farming, e.g. improving animal welfare, reducing environmental impact, and increasing the profitability for farmers. At a certain point, however, there will be trade-offs and decisions to be made about how to prioritize values. Depends on who made the decisions, the decisions will dictate who benefits from these PLF tools and who is disadvantaged by these developments (Werkheiser, 2020). In the current thesis, PLF approaches focus on improving and optimising the current system without questioning the values (or reasoning) behind the existing system. Practically, when comparing different approaches, e.g. PLF-approaches versus bigger changes through re-designing the housing system, the cost of re-designing the housing and related facilities might be much higher than improving the current system by adding sensors. To be safe and keep the business running, ‘optimisation' of the current system seems like a logical approach.

‘Animal welfare’ as part of the consideration has not been mentioned in this chapter. Animal welfare is defined here as the balance between pleasant and unpleasant experiences throughout the life of an animal (FAWC, 2009). The author argues that improving animal health and animal welfare is an added value, but not an initial drive of developing and deploying PLF tools. As discussed, animals (i.e. veal calves) were not taken into consideration in the process of the decision-making, and their needs as sentient beings were consequently not considered in the development of PLF. The difference between ‘improving animal welfare as a consequence’ and ‘improving animal welfare as an initiative’ determines how animals in general are treated. The former (i.e. improving animal welfare as a consequence) considers animals as products (corresponding to the name ‘veal industry’), with the identified problem being ‘a sick calf being identified late’, the solution being ‘detecting a sick calf earlier’. Improving the lung function of the calves, including the immune system and its development, is therefore out of scope. The latter (i.e. improving animal welfare as an initiative) recognises calves as sentient beings, keeping a healthy calf is no doubt a minimum requirement. Only when the need of calves as sentient beings are met (as much as possible), the calves will grow well and produce well. This, however, requires a holistic way of looking at the relationships between human activities (veal production as part of it) and nature (refer to Gaia theory, Latour, 2017). Recently, improving animal welfare has received more and more attention, e.g. from consumers, NGO's and supermarkets, regulations (e.g. 'dierwaardige houderij' in the Netherlands), etc.

The veal industry 'tries' to adapt to these changing requirements to keep the business running. However, this situation has not changed much compared to 15 years ago as described by e.g. Wathes *et al.* (2008). If the industry has first to survive as a business (with low profit) and make practical choices (to save costs), we as the consumers and the public need to think of the forgotten part to complete the loop: what are the consequences? Does the development and deployment of PLF help form a better livestock farming? And is it in line with the efforts to tackle the current crises, e.g. global climate change, global resource depletion, and global inequalities of living standards (Diamond, 2019)? Given the current lack of regulations limiting the development and fast deployment of PLF, further intensification of farms might become real (Werkheiser, 2020), which will also have a major impact, e.g. on the environment. The further consolidation of farms means exactly what Berckmans (2017) visualises: the number of farms decreases, the scale of single farms increases, and the overall production (per animal) increases. Hypothetically, with the support of PLF, the livestock sector reaches the level of production anticipated by Berckmans (2017) for 2050: a 70% increase of animal products (a small part is contributed by veal industry, as introduced in the general introduction). Given that the livestock sector contributes a major part of GHG emissions, it is hard to imagine a 70% increase of animal products with less or equal levels of GHG emissions. Has the potential environmental impact been considered into the value chain in the decision-making process of PLF deployment?

5.4 Summary

The above discussion used three values, i.e. 'profitability', 'animal welfare', and briefly mentioned 'environmental impact', as an example to show the potential risks of developing and deploying PLF to detect issues rather than look into the causes. It is complex to make a choice that balances different interests and values. However, given that 'sustainable farming' is accepted as consensus at different levels (government, public, corporate, etc.), the author invites the readers to start considering how to set up an appropriate value hierarchy, that embraces PLF development and a more sustainable livestock farming without further compromising the environment (Tullo *et al.*, 2019), natural resources, and animal welfare (Rowe *et al.*, 2019; Tuyttens *et al.*, 2022). This requires the efforts of the whole of society, including multi-stakeholder engagement, public-private partnerships, awareness raising and capacity building, strengthening the policy environment, research and innovation, metric-based monitoring and evaluation (One Planet Network, 2020). Suggestions were provided involving different stakeholders, e.g. reflecting consumer perception and consumer choice to the farmers to drive the improvement of rearing conditions (Haskell, 2020), or proposing new framework of the livestock farming system such as ‘animal-centred farming’ (proposed by the research group of Bas Rodenburg, Utrecht University, the Netherlands). In essence, it is possible to avoid the conflict between developing and deploying PLF and incorporating important values into this process, e.g. between animal welfare and efficient farming (Dawkins, 2017), or between animal welfare and sustainable development (Keeling *et al.*, 2021).

To summarise, the current development of PLF tools reflects the veal industry’s value preference, i.e. detecting health issues early and monitoring animal performance to maximize efficiency and production. The initial step of developing PLF tools to assist a more sustainable livestock farming, lies not on developing the techniques, but on re-setting the value hierarchies.

Summary of the thesis

The veal industry was created to make use of the dairy calves that are not wanted or needed for herd replacement, commonly referred to as 'surplus' calves. These calves are typically transporting from different source dairy farms, sometimes across country borders, at the early age of around two to four weeks to a fattening veal farm. This dairy-veal chain presents potential concerns for calf welfare, including transportation of young animals, high risk of disease, and barren housing. One important concern for the farmers in this production system is the high morbidity and high mortality rates, resulting in often a high use of antibiotics at veal farms.

Precision livestock farming (**PLF**) is a promising avenue in the improvement of health care in livestock, and specifically in health monitoring, to assist the conventional health check by farm staff (which often identify a sick calf at a late stage), enabling timely individual treatments and separation of diseased animals, reducing the potential antibiotics use. The advances of PLF make it possible to start developing an automated tool for health monitoring in veal calves: 1) the decreasing cost and increasing implementation of electronic tools allows for the application of 'sensing solutions' on a large scale, such as in commercial veal fattening farms, 2) behavioural and physiological parameters can nowadays be automatically recorded at individual animal level, continuously and over long periods of time, allowing us to follow the course of the whole (or as long as possible) fattening period, 3) previous studies reported automated detection of specific diseases such as respiratory disease, which proved the feasibility of this PLF approach, 4) the advantage of machine learning in this context is that these systems can learn and adapt according to the data, without the need for human input, to develop the most adequate algorithms to describe and predict patterns of data.

The aim of this thesis was to lay the foundations for the development of an automated health monitoring system for veal calves by developing algorithms that help describe and predict calf patterns of behaviour and anatomy. Three paths were followed to achieve this aim:

In **Chapter 2**, we adapted a four-stage approach for developing PLF-based early disease detection tools in veal calves, i.e. 1) sensor technique, 2) data interpretation, 3) information integration, and 4) decision support. At stage one, automatic feeding stations, accelerometers, infrared thermography cameras, microphones, and 3D cameras are accurate in screening behaviour and physiology of calves. At stage two, changes in feeding behaviours, lying, activity, or body temperature corresponded to changes in health status, and point to health

issues earlier than manual health checks. At stage three, accelerometers, thermometers, and automatic feeding stations have been integrated into one system which was shown to be able to successfully detect diseases in calves, including bovine respiratory diseases and neonatal calf diarrhoea. Most studies up to now are at stage one (sensor technique) or stage two (data interpretation), a few studies are at the beginning of stage three (information integration).

Chapter 3 used generalized additive models to describe the group activity patterns in healthy calves and the changes of the patterns over time. The fitted model used the extracted features of acceleration data to describe the activity pattern of 'being active' during the fattening period and we obtained a medium predictive performance. Though individual calves may show different activity patterns in a specific time window, the smooth curve of the group activity pattern over a long period of time is relatively stable, therefore can be used as a valuable reference to compare to the activity pattern of an individual calf. However, the existing computing power limited the depth that we could apply for interpretation of the current dataset. To describe the activity patterns in a more detailed way, e.g. identifying lying, standing, and walking time, exploring different methods to analyse the current dataset is needed. The understanding of activity patterns of healthy calves can be helpful in future to further develop a model identifying the abnormal patterns in individual calves, which give early warnings to farmers.

Chapter 4 explored computer vision and machine learning techniques in estimating body weight (**BW**) of calves using images obtained from top-view RGB-D cameras. Scaled-based BW, taken at three time points during the fattening period, were used as the ground truth. A deep learning object detection method MaskRCNN was trained for detecting the calves in the images, which was found to have an accuracy of 90%. The extracted features in combination with machine learning models, are able to predict the BW of calves with high accuracy. Among the trained models, linear regression obtained the best result using features extracted from the RGB-mask and corresponding depth images with a median relative error of 0.05. However, smooth growth curves in individual calves have not yet been feasible based on the current BW estimation models, especially for predicting previously unseen ranges of BW. Further work is required to improve the performance of the models, e.g. to improve the test set-up, to increase the number of images in the model training, and to ease the process of aligning suitable images.

Based on our proposed framework and our results, this thesis falls in stage two - we reviewed the available sensor technology options available for monitoring calf behaviour and physiology (Chapter 2), described activity patterns of healthy calves using accelerometers (Chapter 3) and tested the efficacy of models applied to 3D images to predict calf BW (Chapter 4).

Chapter 5 summarized and discussed the results of all chapters in an integrated way and identify the potential applications of current results, how it can contribute to alleviate the problem of high antibiotic use and subsequently improve welfare and health, the author also briefly shared the further plan of analysing the current dataset. This thesis focuses on learning about the patterns in healthy calves, which lay the foundations for the next step of detecting 'deviations' of patterns in individual calves. The final goal of these automated health monitoring tools is to detect sickness in calves at an early stage, aiming at reducing the potential anti-biotics appliance, especially at the group level.

Furthermore, along this research approach, the author noticed the risks of developing PLF-based solutions. In Chapter 5, the author challenges the logic behind this approach, points out the missing values in the process of developing and deploying PLF tools, and invite the readers to think about alternatives on how we could reduce the antibiotics use in veal rearing, with a more animal-oriented consideration, to answer the societal demand such as farmers' need, the nitrogen crisis in the Netherlands, to address global crisis including global warming and the global resource depletion, and more importantly, to let PLF be a tool, not the goal.

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Starting 5 years ago, I did not have any expectations of the coming years - thought it would be another ‘experimenting-publishing’ cycle, which might take a bit longer than MSc. Finishing some work, that should be it.

Reflecting now, as the PhD went on, I let go more and more of the obsessions of obtaining the outcomes, instead I used a lot of time to develop ‘useless’ thoughts. This PhD project has been a concrete tool for me to project the concerns and questions raised in my mind - mainly about the relationships: between people, between animals and people, between people and society, between people and nature, etc. Without any satisfactory answers though, I have been knowing myself a bit more, appreciating the relationships I had in this journey with many kind people.

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About the author

After finishing his Master in animal production, Dengsheng Sun continued his study as a PhD student in the field of precision livestock farming and animal behaviour&welfare. He was lucky to be able to develop some thoughts and met people who share similar ideas. He will continue this learning, thinking, and (possibly) sharing journey, within and beyond the scientific domain. In terms of the scientific interest, he will keep learning and exploring the relationships between animals and humans, within the (evolving) context of contemporary farming.

So far, he is doing well on this journey (with a lot of help from friends).

List of publications

Peer reviewed scientific papers

Sun D, Webb L, van der Tol P.P.J., van Reenen K. A Systematic Review of Automatic Health Monitoring in Calves: Glimpsing the Future From Current Practice. Front Vet Sci (2021). 8:761468. doi: 10.3389/fvets.2021.761468

Expected publications

Sun D, Leday G.G.R, van der Tol P.P.J., Webb L, van Reenen C.G. Activity Patterns of Healthy Calves Housed in Large Groups.

Sun D, Afonso M, Antonides S, van der Tol P.P.J., Webb L, van Reenen C.G. Computer Vision-based Body Weight Estimation in Group-housed Calves.

PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review/project proposal (9 ECTS)

- A systematic review of automatic health monitoring in calves: glimpsing the future from current practice
- Sensor-based decision support system for health monitoring in calves

Post-graduate courses (12.6 ECTS)

- Basic statistics; PE&RC (2018)
- Advanced statistics course design of experiments; WIAS (2018)
- The fundamentals of animal emotions; WIAS (2019)
- Introduction to R for statistical analysis; PE&RC, SENSE (2019)
- R markdown; WGS (2021)
- Tidy data transformation and visualization with R; PE&RC (2021)
- Animal welfare and the UN sustainable development goals; Swedish University of Agricultural Sciences (2021)
- Linear models; PE&RC (2022)
- Mixed linear models; PE&RC (2022)
- Generalized linear models; PE&RC (2022)
- Multivariate analysis; PE&RC (2023)

Invited review of (unpublished) journal manuscripts (1 ECTS)

- Journal of Dairy Science: early disease detection in calves (2022)

Competence strengthening/skills courses (3.9 ECTS)

- Brain training; WGS (2019)
- Competence assessment; WGS (2019)
- Scientific integrity & ethics in animal science; WIAS (2019)
- Scientific writing; WGS (2020)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.5 ECTS)

- PE&RC First years weekend (2019)
- PE&RC Day (2018, 2019)

Discussion groups/local seminars or scientific meetings (6.1 ECTS)

- Towards healthy & sustainable food systems in an urbanising world (2018)
- WUR resilience symposium (2019)

- Animal welfare and adaptation discussion group (2019)
- Global one health past, present and future (2019)
- WIAS Annual conference (2020, 2021)
- European conference on precision livestock farming & international conference on precision dairy farming (2022)

International symposia, workshops and conferences (4.3 ECTS)

- WIAS Annual conference; poster presentation; the Netherlands (2019)
- 8th International conference on the assessment of animal welfare at farm and group level; poster presentation; Ireland (2021)
- ISAE 56th International congress; poster presentation; Estonia (2023)

Lecturing/Supervision of practicals/tutorials (0.3 ECTS)

- Summer school from farm to fork new trend and technologies; WUR (2021)

BSc/MSc thesis supervision (3 ECTS)

- Early detection of fever in veal calves using automatic obtained sensor data
- Early detection of respiratory disease in veal calves using automatic obtained sensor data
- Assessing health of pre-weaned calves using videos
- Early disease detection in veal calves using automatic obtained sensor data
- Automatic health monitoring in calves using 3-D cameras and automatic milk feeders
- Computer vision based calf growth monitoring

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