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A systematic literature review on the use of machine learning in precision livestock farming

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ABSTRACT

This article presents a systematic literature review of recent works on the use of machine learning (ML) in precision livestock farming (PLF), focusing on two areas of interest: grazing and animal health. This review: (i) highlights opportunities for ML in the livestock sector; (ii) shows the current sensors, software and techniques for data analysis; (iii) details the increasing openness of data sources. It was found that the use of ML in PLF is in a stage of development and has several research challenges. Examples of such challenges are: (i) to develop hybrid models for diagnosis and prescription as a tool for the prevention and control of animal diseases; (ii) to bring together the grazing and animal health issues; (iii) to give autonomy to PLF using autonomous cycles of data analysis tasks and meta-learning; and (iv) to bring together soil and pasture variables because, for both, animal health and animal grazing, the variables used are only behavioral and environmental.

1. Introduction

In traditional livestock farming, animal species are bred, and products for human consumption are obtained; for instance, meat and milk. Overall, livestock provides 33% percent of the protein consumed in the human diet (Suryawanshi et al., 2017). Recently, it has emerged the concept of *Precision Livestock Farming (PLF)*: A holistic approach that adds *information and communication technologies (ICT)* to improve the farming process. PLF plays an important role in the fourth industrial revolution, also known as Industry 4.0. PLF uses ICT to reduce investment costs and increase both, production and animal health (Banhazi et al., 2012).

In traditional livestock farming, decisions are often based –only– on the experience of the producer. In PLF, such decisions are based on quantitative data, such as liters of milk per milking. In addition, quantitative data can be obtained in real-time. To obtain and study such data, in real-time, PLF systems use data analysis, *machine learning (ML)*, control systems, and ICT (Banhazi et al., 2012).

The main objectives of PLF are: (i) to identify the most appropriate livestock feeding, (ii) reduce environmental impact through efficient resource management, (iii) manage crop processes to make a perfect synergy with livestock feeding, (iv) ensure food safety through traceability (documentary record from production to consumption) of products, and (v) improve animal health and crop efficiency (Pomar et al., 2011).

PLF must improve the efficiency of production systems. To improve efficiency, it is essential to, correctly, manage data generated every day in livestock farms (Suryawanshi et al., 2017). To manage data, such systems must perform collection, processing, analysis and distribution of information. A correct data management can result in improved productivity, in terms of grazing lot management, livestock nutrition, and animal health.

Technology over the years has made easier to carry out traditional farm activities. Specifically, in livestock production, it is now possible to process data collected daily related to animal control (Vranken and Berckmans, 2017). ICT applied to the livestock sector has made possible to exploit this data to predict and describe the behavior associated with a more efficient animal production (Espinosa et al., 2016). To make such predictions, ML is often used. In general, this information about animal behavior allows determining the needs of the animals, providing personalized and optimal attention for the benefit of the production (Banhazi and Black, 2009).

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At present, PLF seeks, through technological solutions in agricultural and livestock production systems, to supply adequate food for the expected world population of more than nine billion inhabitants by 2050 (Perakis et al., 2020). PLF allows the sector to be extended to sustainable livestock production, by considering production and animal health. In addition, PLF allows producers to maintain an optimum number of animals per farm, find prompt solutions to animal diseases, and define a more efficient production model (Berckmans, 2014). In this context, a *systematic literature review (SLR)* is needed to determine the state-of-the-art in PLF related to artificial intelligence, and, in particular, current ML techniques used in PLF, and the challenges for the following years.

To understand ML approaches and challenges, in the following years, in the context of PLF, two aspects are discussed in this paper. Firstly, a review on the state-of-the-art of PLF based on the following topics: works on ML for grazing and for animal health. According to Van der Burg et al. (2019), these two topics represent research challenges in the field of PLF. Secondly, a discussion of current challenges for PLF related to ML.

The main contributions of this article are the following. First, a presentation of the most widely used ML techniques, in the last five years, for the analysis of grazing and animal health. Second, an overview of the most used techniques of PLF data acquisition in the literature. As a final result, an overview of the works related to ML and PLF, and future research directions according to our analysis of the previous researches.

The rest of this article is organized as follows. Section 2 introduces the methodology of the SLR, including an analysis for the need of a new SLR in PLF. Section 3 presents the results of the review. Finally, Section 4 concludes the document by a general discussion around how the research questions have been answered, and presents the current limitations and challenges.

2. Methodology

The methodology used is of SLR, which divides the process into four phases (Torres-Carrion et al., 2018): (i) identification of the need for revision, (ii) definition of a review protocol, (iii) conducting the review, and (iv) development of an analysis of the review.

In the first phase, the goal is to identify why a new SLR is needed in the domain. In the second phase is set up the information collection process. For that, it is specified the questions that guide the research and the search strategies; the criteria for the inclusion or exclusion of documents, the evaluation of the relevance and quality of the documents; and, finally, the queries for academic data sources. In the third phase is carried out an exhaustive review of each document to determine if such documents answer the research questions. Documents that do not meet the expected characteristics are discarded. Finally, in the last phase is presented a general analysis for each research question.

2.1. Identification of the need for revision

In this section, previous SLRs in the domain of PLF are presented. The reviews analyzed in this section are summarized in the following categories: models for farming enterprise, interoperable standards in extensive livestock farming systems, dairy energy, and animal health and animal monitoring.

2.1.1. Models for farming enterprise

O'Grady et al., in O'Grady and O'Hare (2017), presented an overview of models for a farming enterprise. Some examples of the models are *Great Plains Framework for Agricultural Resource Management (GPFARM)*, from North America, applied to the entire farm domain; GRAZPLAN, from Australia, applied to grazing enterprises; EcoMod, from Australia and New Zealand, applied to pasture management; *Agricultural Production Systems Simulator (APSIM)*, from Australia, used for crop modeling; *National Research Council (NRC)*, from North America, focused on nutrition animal factors; *Nordic feed evaluation system (Norfor)*, from Scandinavia, focused on nutrition animal and feed factors; *Total Dry Matter Intake Index (TDMI)*, from Finland, implemented for nutrition dry matter Intake animal and feed factors; Biopara-Milk, from the United Kingdom; and, finally, Karoline, from Scandinavia, used to analyze the impact of feeding on rumen pH in dairy cow for their nutrition, milk production, digestion, and gas emissions. GRAZPLAN, EcoMod and APSIM models are focused on grazing, pasture and crops, respectively. O'Grady et al. expressed that the difficulty of adoption of these models, by individual farmers and agricultural enterprises, depends on the usability and the identification of best practices in their activities.

2.1.2. Interoperable standards in livestock farming systems

Bahlo et al. (2019) reviewed interoperable standards in extensive livestock farming systems, and concluded that there is a need for a new type of decision support tool. Bahlo et al. argued that both, farm-centric and farmer-centric approaches are needed. Particularly, they also concluded that a consensus is needed on data exchange standards to prove the value of shared data at the farm scale (commercial benefit) and a regional scale (public good).

2.1.3. Dairy energy

Shine et al. (2020) focused on summarizing and reviewing dairy-energy research from the monitoring, prediction, and analysis points of view. According to Shine et al., dairy-energy prediction models have been frequently used throughout the literature to conduct dairy- energy analysis, and to estimate the impact of changes in the infrastructural equipment and managerial practices.

2.1.4. Animal health

On the domain of animal health, Mcloughlin et al. (2019) discussed current trends in sound analysis for ecology and conservation. Mcloughlin et al. detailed the vocalizations produced by three of the most important farm livestock species: chickens (*Gallus gallus domesticus*), pigs (*Sus scrofa domesticus*) and cattle (*Bos taurus*). Mcloughlin et al. described methods to monitor animal health based on the sound, with the potential to be automated for large-scale farming. In addition, Benjamin and Yik (2019) conducted a review aimed at veterinarians and pig specialists, describing machine learning algorithms, such as pig-face recognition –using convolutional neural networks. They also identified the most relevant sensors for measuring animal health: cameras (2D and 3D), microphones, thermistors and accelerometers. Finally, they discussed how these technologies can be used to improve pig health.

2.1.5. Animal monitoring

Recent technologies to monitor animals are based on machine-learning and computer-vision algorithms. There are four SLRs focused on animal monitoring. First, Norton et al. (2019) discussed the main technology-oriented approaches to animal monitoring and showed how image and sound analysis can be used to build *digital representations* of animals. Second, Milan et al. (2018) proposed a discussion on how ML algorithms could be used to monitor internal and surface temperatures, breathing rate, sweat rate, gait pattern, behavior, physical dimensions, weight and body-condition score of dairy cows. Third, Astill et al. (2020) discussed the areas of impact that new smart-sensor technologies will have on poultry operations, and described how sensor technology is related to big-data analytics and the *Internet of Things (IoT)*, and how these technologies can enhance the productivity of the poultry industry. Finally, Dominiak and Kristensen (2017) presented methods that classify or prioritize the alerts that occurred in the herds. They suggested that future researches should focus on alternative approaches of detection models, using the prior probability or risk of a condition to occur.

2.1.6. Summary

Table 1 shows the problems addressed by recent literature reviews on PLF. In general, the tasks related to PLF have focused on the

Table 1
Summary of recent SLRs.

Article	Objective
O'Grady and O'Hare (2017)	Successful enterprise farm models.
Bahlo et al. (2019)	Interoperable data standards in farming systems.
Shine et al. (2020)	Dairy energy for monitoring, prediction and analysis.
Mcloughlin et al. (2019)	Sound classification for ecology and conservation.
Benjamin and Yik (2019)	Pig health with sensors and ML.
Norton et al. (2019)	Image and sound to build digital animal-representations.
Milan et al. (2018)	Precision dairy farming.
Astill et al. (2020)	New sensor technologies on poultry operations.
Dominiak and Kristensen (2017)	Methods that prioritize alerts occurred in the herd.

classification of animal behavior and monitoring; nonetheless, previous literature reviews do not analyze the use of ML in grazing and animal health like contexts of application. Our article reviews different ML techniques, on the context of PLF, that have been used for the analysis of grazing and animal health, as well as the different forms of data acquisition for training such ML models. Thus, there are no SLRs about the use of ML models in PLF nor in the context of grazing and animal health.

2.2. Document selection process

In this section, activities carried out for the SLR are introduced. First, research questions and search strategies are presented. Second, document selection, inclusion and exclusion criteria are explained. Finally, quality evaluation and a summary of the selection process are detailed.

The research questions, in the two areas of interest of this research, are: (i) How have systems for grazing been developed based on ML in PLF? and (ii) How has ML been used for animal health in PLF? The keywords for these questions are summarized in Table 2.

The boolean search equations generated for this SLR combine the previous keywords to answer each research question. The sources used were Google Scholar, IEEE Xplore, Scopus and Springer databases. Search equations are summarized in Table 3. The initial documents, obtained with these search equations, were 171.

Table 4 shows the inclusion and exclusion criteria used in this SLR. Each inclusion criterion is assigned a nomenclature CIi.

Table 5 shows the results after applying the inclusion and exclusion criteria to the queries in Google Scholar, IEEE Xplore, Scopus and Springer databases. The total was of 54 articles, for the period from 2015 to 2020.

In what follows, a set of questions is presented to ensure the quality of the documents related to each research question. Such questions allow evaluating the quality of the documents. With respect to ML, for grazing in PLF, there are two questions for quality evaluation: (i) Does the document explain the use of ML in grazing? and (ii) Does the document describe a PLF management system based on ML? With respect to ML for animal health in PLF, the questions are: (i) Does the document describe how ML enriches data collection in animal health in PLF? and (ii) Does the document describe how sensors are used to measure animal health in the context of PLF?.

Fig. 1 shows the selection process to find the relevant works for this research.

For question on ML for grazing, the quality assessment left 15 works; and for question on ML for animal health, the quality assessment left 20. At the end of the selection process, there was a total of 35 documents to be analyzed.

Table 2
Terms or keywords for the research equations.

Precision Livestock Farming			
A1	Animal health	**A2**	Precision livestock farming
A3	Animal welfare	**A4**	Grazing
Machine Learning			
B1	Machine learning	**B2**	Big data
B3	Data models		

Table 3
Search equations for each research question.

Question	Search equation	Documents
Grazing	A4 AND A2 AND (B1 OR B2 OR B3)	92
Animal Health	(A1 OR A3) AND A2 AND (B1 OR B2 OR B3)	79
	Total	171

Table 4
Inclusion and Exclusion Criteria.

Inclusion Criteria	CI1 Scientific articles, conference proceedings. CI2 Publications are in English CI3 Publications after the year 2015 CI4 Belong to sub-area of Computer Science CI5 Belong to sub-area of Engineering
Exclusion Criteria	Publications before 2015. Non-digital publications. Publications not available for full review.

Table 5
Summary of equations for the research questions after inclusion and exclusion criteria.

Question	Search equations with inclusion and exclusion criteria	Result
Grazing	(A4 AND A2 AND (B1 OR B2 OR B3)) AND CI1 AND CI2 AND CI3 AND CI4 AND CI5	26
Health	(A1 OR A3) AND A2 AND (B1 OR B2 OR B3)) AND CI1 AND CI2 AND CI3 AND CI4 AND CI5	28
	Total Documents	**54**

2.3. Preliminary results

The preliminary results are divided into two parts. First, the results regarding ML for grazing in PLF and, after, the results regarding ML for animal health in PLF.

2.3.1. Machine learning for grazing in the PLF context

The purpose of grazing is: (i) to maintain a high production of good quality fodder for the longest period of time, (ii) to maintain a favorable balance between fodder species, and (iii) to obtain an efficient utilization of the fodder produced, achieving a profitable livestock production (Bell et al., 2014).

Regarding the question of how ML has been used to improve grazing in PLF, 15 documents were selected, from which 12 are in journals and 3 are in conferences. Fig. 2 shows Australia with the largest production of documents focused on grazing and, especially, on sheep. The largest production of documents may be the impetus given by the *cooperative research center (CRC) program* that has developed, in recent years, improvements in technologies for identification and electronic registration, allowing farmers to manage their sheeps with greater accuracy. The Australian farmers weigh their animals frequently. Live weight –and its variations in time– give farmers a good idea of the nutritional status of the animals. The use of electronic precision scales, with *radio frequency communication interface (RFID)* and data-storage equipment, transforms a tedious process –with numerous errors– into something simple, fast and natural (Caja et al., 2016).

The United States is the country that produces the most beef in the world: 12,700 metric tons of beef. Such a production is followed by Brazil, with 10,000 tons (Porter, 2019). In most of these countries, beef

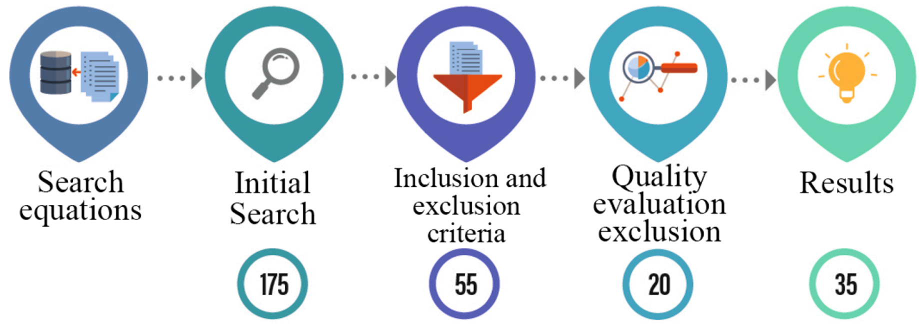

Fig. 1. Selection process of articles for the SLR.

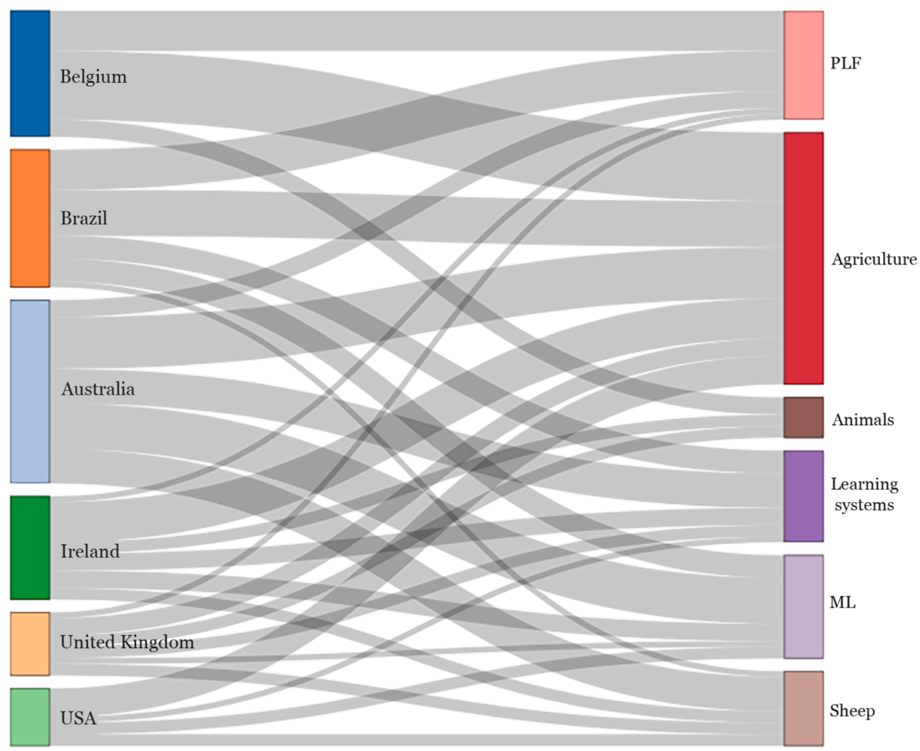

Fig. 2. Countries by keywords for the research question of ML for grazing in PLF.

exports also have a great weight in their economies; for this reason, researches on PLF, ML and pasture agriculture –in these countries– is very important, as shown in Fig. 2.

2.3.2. Machine learning for animal health in the PLF context

Animal health is the state of an animal to cope with its environment. Animal health is related to all coping mechanisms, involving the physiology, behavior, feelings and the responses to pathologies (Machado and Silva, 2019). Ensuring a safe, sufficient and nutritious food supply for a population that is increased so rapidly, depends on healthy and productive animals (Overgaauw et al., 2020).

Regarding the question of how ML has been used to improve animal health in the PLF domain, 20 documents were selected, of which 11 are in journals, 8 are in conferences and 1 is a literature review. Fig. 3 shows that there is widespread interest in this issue, demonstrated by the growing public concern for animal health in most countries of the world. Animal health is an important part of well-being (Singer et al., 2019). Not surprisingly, countries such as Brazil, China, and Australia, which have a large production of meat, are interested in measuring behavior and monitoring well-being, using ML techniques. Measuring behavior and monitoring well-being helps them to increase production and export a higher-quality product.

3. Review report

The results are divided into two parts. First, the results regarding ML for grazing, in the PLF context, and, after, the results regarding ML for animal health in the PLF context.

3.1. Machine learning for grazing in PLF

In this section, the analysis of the documents is divided into works about the classification of animal behavior and about the animal monitoring.

3.1.1. Classification of animal behavior

The following documents focus on the classification of animal behavior. The first category describes the documents that focus on how to classify livestock behavior in general. The second category presents documents –specifically– on the classification of grass intake and rumination activities.

Livestock-behavior classification. Animal behavior can be

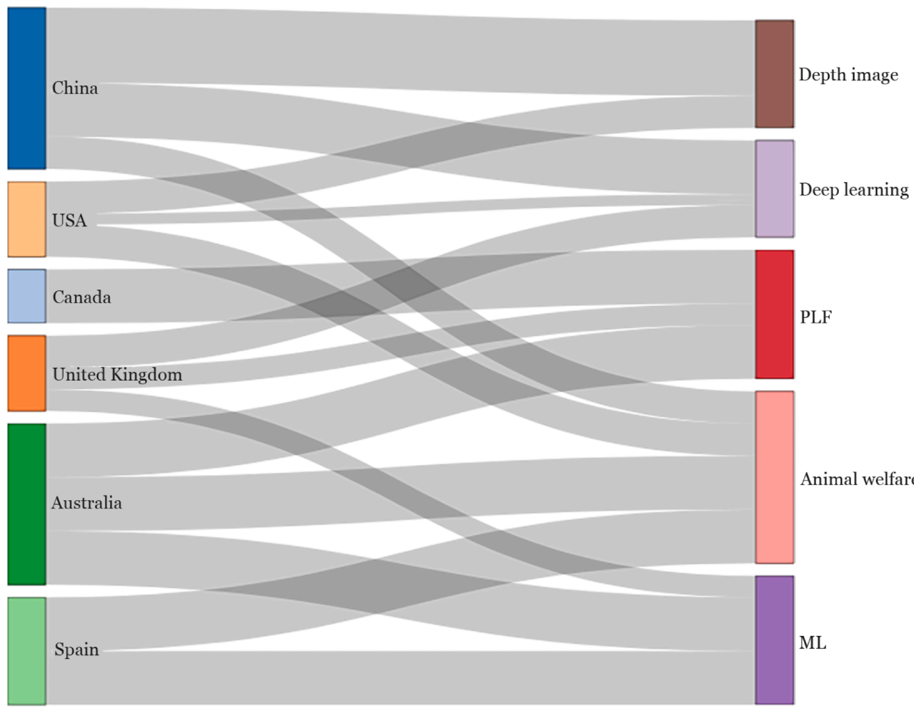

Fig. 3. Countries by keywords for the research question of ML for animal health in PLF.

classified into different categories and with different sensors. Vázquez-Diosdado et al. (2019) presented a combined offline *k-nearest neighbors (KNN)* algorithm and an online learning algorithm, which is deemed by the authors as a useful mechanism for long-term in-the-field monitoring systems. The proposed algorithm classifies relevant sheep behavior using information from an embedded edge device that includes a tri-axial accelerometer and tri-axial gyroscope sensors.

Another alternative to KNN algorithm for behavior classification is a hierarchical ML. Suparwito et al. (2019) proposed the use of a hierarchical ML method to classify livestock behavior. Firstly, they classified livestock behavior into two behavioral categories: active or inactive. Each of the two categories is then broken down at the next level into more specific behavioral categories. Secondly, they tested the proposed methodology using two commonly used classifiers: *Random Forest (RF)*, *Support Vector Machine (SVM)* and, a newer approach, *Deep Belief Networks (DBN)*. Finally, results showed that the hierarchical classification technique works better than the conventional approach.

Further than the classification of behavior in active or inactive, one can classify behavior using an inventory of actions exhibited by animals. Such inventory is known as an *ethogram*. Fogarty et al. (2020) explored feature creation and ML algorithms to provide the most accurate behavioral classification using an ear-borne accelerometer in extensively-grazed sheep. Nineteen derived-movement features, three epochs (5, 10 and 30 s) and the next four ML-algorithms, were assessed: *Classification and Regression Trees (CART)*, SVM, *Linear Discriminant Analysis (LDA)* and *Quadratic Discriminant Analysis (QDA)*. The behavior classification was also evaluated using three different ethograms, including detection of (i) grazing, lying, standing, walking; (ii) active and inactive behavior; and (iii) body posture. The detection of the four mutually-exclusive behaviors (grazing, lying, standing and walking) was the most accurately performed, using a 10 s epoch, by SVM (76.9%). The most accurately was detected, using a 30 s epoch, by CART (98.1%). LDA, using 30 s epoch, was superior for detecting posture (90.6%).

The concept of ethograms used in sheep can also be extended to dairy cows. Vázquez D. et al. (2015) developed a DT algorithm that uses tri-axial accelerometer data from a neck-mounted sensor to classify biologically important behavior in dairy cows and detect transition events between lying and standing. Data was collected from six dairy cows that were monitored, continuously, for 36 h. Direct visual observations of each cow were used to validate the algorithm. The results show that the DT algorithm is able to –accurately– classify three types of biologically relevant behaviors: lying (77.42% sensitivity, 98.63% precision), standing (88.00% sensitivity, 55.00% precision), and feeding (98.78% sensitivity, 93.10% precision). Transitions between standing and lying were also detected –accurately– with an average sensitivity of 96.45% and an average precision of 87.50%.

Another approach to define an ethogram is using unsupervised learning. The objective of Achour et al. (2019) was to develop an effective unsupervised-classification model of data collected by *Inertial Measurement Units (IMU)*, attached to the back of dairy cows housed in free-stall. Data was aggregated according to different sampling frequencies and segmentation windows. The different times of lying, standing, lying down, standing up, walking and stationary behaviors were observed and recorded in real-time. The designed classification model is based on univariate and multivariate *Finite Mixture Models (FMM)* and DT. The valid transitions between standing and lying behaviors are guaranteed by constraints imposed by a deterministic finite-state automaton. The obtained results revealed that 99% of behaviors are well classified. Standing, lying on each side and changing between these positions are classified with 100% accuracy, followed by stationary with 99% sensitivity, 96% specificity, 99% precision, and 99% accuracy. The walking behavior is classified with 96% sensitivity, 99% specificity, 91% precision, and 98% accuracy.

GPS data is also an important source of information for behavior classification. In the work of Williams et al. (2019), they presented variable segmentation applied to GPS data gathered from 30 dairy cows at pasture. Using these segments, the performance of 13 ML algorithms (base learners) implemented in *Waikato Environment for Knowledge Analysis (WEKA)* were compared using default parameters in classifying grazing, resting and walking. Two stacking ensembles were then derived using the WEKA implementations. The first ensemble contained the best performing base learners. The second ensemble was an optimized version derived using a manual ensemble selection method. Both versions of the ensemble were evaluated on an independent test set derived from 10 cows. The ensembles performed well using base learners based on boosting algorithms: *Simple logistic (SL)*; *Logistic model trees (LMT)*, MLP, *Naive Bayes(NB)*, DT, SVM, *Naive Bayes tree (NBTree)*, *Logistic model trees (LMT)* and *Sequential minimal optimization (SMO)*.

Grass intake and rumination. Some researches have focused –specifically– on the classification of behavior related to grass intake and rumination. Andriamandroso et al. (2017) proposed an open algorithm, named *Statistical Model (SM)*, for the detection of cattle's grass intake and rumination activities. They mounted a smartphone on 19 grazing cows of different breeds, and recorded daily video sequences on the pasture of different forage. The final algorithm uses the average value and the standard deviation of two signals in a two-step discrimination tree: The gravitational acceleration on the x-axis (Gx) expressing the cows head movements, and the rotation rate on the same x-axis (Rx) expressing jaw movements. Validation on an independent database resulted in an average detection accuracy of 92% with a better detection for rumination (95%) than for grass intake (91%).

Another approach to the classification of actions, related to grass intake and rumination, is presented as follows. Chelotti et al. (2018) presented a new algorithm, called *Chew-Bite Intelligent Algorithm (CBIA)*. CBIA uses concepts and tools derived from pattern recognition and ML. CBIA includes: (i) a signal conditioning stage to attenuate the effects of noises and trends, (ii) a pre-processing stage to reduce the overall computational cost, (iii) an improved set of features to characterize jaw-movements, and (iv) a ML model to improve the discrimination capabilities of the algorithm. Three signal conditioning techniques and six ML models are evaluated. The overall performance is assessed on two independent data sets, using metrics like recognition rate, recall, precision and computational cost. The results demonstrated that CBIA achieves a 90% recognition rate, with a marginal increment of computational cost. Compared to the algorithms *Least Mean Squares (LMS)*, *Empirical Mode Decomposition (EMD)*, *Multilayer Perceptron (MLP)*, *Decision Trees (DT)* and SVM, CBIA improves the recognition rate by 10%, even in difficult scenarios.

The following work presents a different kind of study, in which they evaluate the effect of rumination and grass intake of different pastures. Alvarenga et al. (2020) developed a classifier of biting and chewing activities of sheep during grazing. Two studies were conducted. The first study evaluated the effect of two diverse pasture species on feeding behavior using micro-sward boxes: forage oats and perennial ryegrass. Two 4-year-old Merino ewes grazed each species, for approximately four, two-minute sessions, over two separate days, one week apart. In the second study, the effect of sward height was investigated using nine plots of ryegrass with three different sward heights, grazed by three 3-year old Merino ewes, for 10 min each. Forty-four features were calculated, from the acceleration signals, and used to classify behaviors using a DT algorithm to determine model accuracy, sensitivity, specificity, and precision. For the micro-sward study, bite activity was classified with a precision of 90.5% for the evaluation data set; whereas, for the validation data set, it was classified with a precision of 98.1% for the 5 s time interval. Accuracy of the DT model increased as time interval increased for both data sets.

There is research focusing –specifically – on the ingesting behavior for different grasses. Campos et al. (2018) presented a method to classify the ingesting behavior of ruminants by means of *Surface Electromyography (sEMG)* signal of the masseter muscle. Despite the similar properties of the grasses, the food-recognition results were reasonable. Feeding and rumination were discriminated with relatively high accuracy. The whole data acquisition, instrumentation and pattern recognition system follow the sequence outlined in Fig. 4. The evaluated classifiers methods applied to EMG pattern recognition are: LDA, QDA, SVM, *Multilayer-Perceptron Neural Network (MLP-NN)*, *Radial-Basis-Function Neural Network (RBF-NN)* and KNN. The MLP-NN was the classifier with the highest mean accuracy for almost every scenario and feature set.

In Fig. 4, the cattle are in rumination, and through the sEMG sensor, data is acquired. After, through signal processing, data is segmented. Such characteristics are created and a classification algorithm is used to be able to predict the animal's intake.

3.1.2. Animal monitoring

Documents focused on animal monitoring are divided into and general monitoring, monitoring calving and estrus, monitoring ingesting behavior, and muzzle-point recognition.

General monitoring. The following work presents a platform of general-purpose for animal monitoring. Debauche et al. (2019) proposed a lambda-cloud architecture coupled to a scientific sharing platform used to archive, and a process of high-frequency data processing is proposed to integrate future developments of the *Internet of Things (IoT)*, applied to the monitoring of domestic animals. An application to the study of cattle behavior on pasture-based on data recorded with the IMU of iPhone 4s is exemplified. The package comes with a web interface to encode the actual behavior observed on videos and to synchronize observations with the sensor signals.

There is general-purpose monitoring application based on computer vision and drones, proposed by Andrew et al. (2017). They explained that computer vision can use deep neural architectures, which are well-suited to perform automated Holstein Friesian cattle detection. They introduced a video processing pipeline composed of standard components, to efficiently process dynamic herd footage filmed by *Unmanned Aerial Vehicles (UAVs)*. They showed that Friesian cattle detection and localization can be performed robustly with an accuracy of 99.3% with this data. They evaluated the individual identification, exploiting coat uniqueness on 940 RGB stills taken after milking in-barn (89 individuals, accuracy = 86.1%). They also evaluated identification via a video processing pipeline on 46,430 frames (approx. 20 s length each) of UAV footage taken during grazing (23 individuals, accuracy = 98.1%).

Calving and estrus. For better management of animal health, it is required to know the exact time when calving and estrus occur. Benaissa et al. (2020) used *Logistic regression (LR)* models and data from calving and estrus sensors. The detection performance within different time intervals (24 h, 12 h, 8 h, 4 h, and 2 h) before calving was investigated. In general, for both calving and estrus, the performance of the detection, within 24 h, was lower than for 8 h-24 h. However, the use of a combination of sensors increased the performance for all investigated detection time intervals. For calving, similar results were obtained for

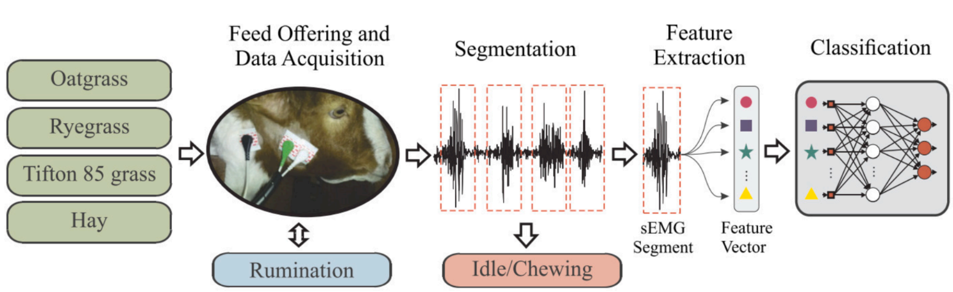

Fig. 4. Complete animal sEMG processing: data acquisition, signal segmentation, feature extraction and classification (Campos et al., 2018).

the detection within 24 h, 12 h, and 8 h. When one sensor was used for calving detection, within 24–8 h, the localization sensor performed best (Precision 73–77%, Sensitivity 57–58%, *Area under the receiver operating characteristic curve [AUC]* 90–91%), followed by the leg-mounted accelerometer (Precision 67–77%, Sensitivity 54–55%, AUC = 88–90%) and the neck-mounted accelerometer (Precision 50–53%, Sensitivity 47–48%, AUC = 86–88%). As for calving, the results of estrus were similar for the time intervals 24 h-8 h. In this case, similar results were obtained when using any of the three sensors, separately, as when combining neck and leg-mounted accelerometers (Precision 86–89%, Sensitivity 73–77%). For both calving and estrus, the performance improved when localization was combined with either, the neck or leg mounted accelerometers, especially, for sensitivity (73–91%).

Ingesting behavior. In monitoring, the goal is not to classify the action during grass intake or rumination, but also to estimate the amount of fiber intake. Campos et al. (2019) proposed a non-invasive method for fiber intake estimation on ruminants. Campos et al.'s method used a sEMG-based sensor system. In order to acquire bite/chewing sEMG signals, superficial disposable electrodes were placed on three uncastrated male goats' masseter muscle, housed in individual pens, and data was sampled during eating using an analog-to-digital converter. Feed samples and-left-overs were weighed before and after the experiment, respectively, to estimate the total intake. Electromyographic preprocessed data was sent to a computer, where seven signal features were extracted. Feed intake was modeled by fitting sEMG features as a predictor by means of a linear model. The results indicated that fiber intake could be successfully predicted in goats eating several forages (Tifton 68 and Tifton 85 grass hay, bad quality Tifton hay, and forage oat hay) with *a coefficient of determination (R2)* higher than 0.867, using a signal feature called *Slope Sign Change (SSC)* as a predictor. SSC expresses signal frequency characteristics and indicates the physiological aspects of bite/chewing.

Muzzle-point recognition. Kumar et al. (2017) have focused on a very particular topic of great interest in cattle. They proposed a muzzle-point recognition based on *Fisher locality*, using a projection algorithm for the recognition of cattle in real-time. They have captured images of animals, using a surveillance camera, and transferred them to the server by wireless network technology. The efficacy of the proposed muzzle-point recognition approach for cattle yields 96.87% recognition accuracy for identifying individual cattle. The proposed approach has a 10.25 s recognition time for enrollment and identification of individual cattle on different sizes of muzzle-point images.

3.2. Machine learning for animal health in PLF

In this section, the analysis of the documents is also divided into the classification of animal behavior and animal monitoring.

3.2.1. Animal behavior

The following documents focus on the classification of animal behavior. This section is divided into two parts. First, general works of animal-behavior classification for livestock and, after, some specific to sow's behavior are presented.

General-livestock behavior. Some works are focused on behavior classification for livestock in general. As an example, Dominiak and Kristensen (2017) proposed three methods to classify or prioritize alerts: *Fuzzy Logic (FL)*, *Naive Bayesian Network (NBN)* and *Markov Hidden Phase model*. NBN shows the greatest potential for future reduction of alerts from sensor-based detection models in livestock production.

Bishop et al. (2019) described another approach to classify behavior based on livestock vocalization. They proposed a multi-purpose livestock vocalization classification algorithm using audio-specific feature extraction techniques and ML models. A comparison of *Mel-Frequency Cepstral Coefficients (MFCCs)* and *Discrete Wavelet Transform (DWT)*-based features was conducted. Classification was determined using a SVM model. High accuracy was achieved for all data sets (sheeps: 99.29%, cattles: 95.78%, dogs: 99.67%). Computational timing reveals that the DWT-based features are faster; such features decrease by 14.81 – 15.38% execution time.

Sow's behavior. In order to control sow's health, an approach is to detect and classify sow's actions using images. Lao et al. (2016) described a computational algorithm for the analysis of depth images, and presented its performance in recognizing the sow's behaviors as compared to manual recognition. The images were acquired at 6 s intervals on three days of a 21-day lactation period. Based on the analysis of the 6 s interval images, the algorithm had the following accuracy in the classification: 99.9% in lying, 96.4% in sitting, 99.2% in standing, 78.1% in kneeling, 97.4% in feeding, 92.7% in drinking, and 63.9% in transitioning between behaviors. According to Lao et al., the lower classification accuracy, for the transitioning category, presumably, stemmed from insufficient frequency of the image acquisition.

Another approach to classify sow's behavior is using a Kinect sensor to identify sow's postures. Zheng et al. (2018) developed a detection system that consists of a Kinect v2 sensor that acquires depth images and a program that identifies sow postures. The depth images of the testing data set of a sow were acquired at 5 frames per second in 24hours on the 15th day of postpartum, and the training data set was collected by some different sows. Since the identification performance from RGB images are impacted by the color and illumination variations caused by an in situ heat lamp and day-night cycle, Zheng et al. showed that the automatic detection from depth images could avoid disturbances of the light. Zheng et al. (2018) found that the sow spent a greater amount of time in recumbency (92.9% at night and 84.1% during the daytime), as compared with standing (0.4% at night and 10.5% during the daytime) and sitting (0.55% at night and 3.4% during the daytime). According to Zheng et al., statistically, the sow's activity level is non-uniform in 24-h of a day, and its preferred lying positions are accordant with the pen's floor design.

3.2.2. Animal monitoring

For animal monitoring, the works are divided into three tasks. First, general works on animal monitoring are presented. After, works related to lameness monitoring are detailed. Finally, present works related to respiratory problems are introduced.

General monitoring. In the previous section, how vocalization can be used for behavior vocalization was presented. Vocalization can also be used for animal monitoring of thermal comfort. Du et al. (2020) developed a vocalization detection method, based on ML, to assess thermal-comfort condition. For extraction of the vocalizations, nine source-filters related temporal and spectral features were chosen, and a SVM-based classifier was developed. As a result, the classification performance of the SVM model was 95.1 ± 4.3% (the sensitivity parameter) and 97.6 ± 1.9% (the precision parameter). Based on the developed algorithm, Du et al. illustrated that a significant correlation exists between specific vocalizations (alarm and squawk call) and thermal comfort indices (temperature-humidity index, THI).

As another alternative to vocalization is to monitor movement and speed because such variables can explain an animal's well-being. Doulgerakis et al. (2019) presented an automated system with a single type of wireless sensor to record indicators of an animal's well-being: movement, speed and geolocation of the animal. Their system was made with a low implementation cost, based on *Deep Neural Networks (DNN)*-pattern-recognition algorithms. According to Doulgerakis et al., the solution provides end-users (farmers) with usable and effective information visualization, so that they take proper actions.

Deep learning has shown to be a technique very useful in animal monitoring. On the one hand, Fonseca et al. (2019) developed a model to predict stress in piglets, monitoring skin temperature using an infrared camera. A total of 40 piglets (20 males and 20 females), from 1 to 22 weeks, under different stress conditions, had the skin temperature recorded during the farrowing and nursery phases. The stresses studied were hunger, pain, thirst, heat/cold, and the normal. The attributes considered, in the analysis were classified using data mining, with stress condition as the target. They used a DT classifier to predict the stress condition, and found that the pain and thirst attributes had better precision, in the model, with the maximum-surface temperature and the sex of the pig.

Another work using deep learning is that of Cowton et al. (2019). They combined a deep-CNN object-localization method, named R-CNN, with two potential real-time multi-object tracking methods, to create a system that can –autonomously– localize and track individual pigs. Cowtom's et al. captured data using RGB cameras. Their system is able to: (i) localize pigs in individual frames, with 0.901 mean average precision, (ii) track individual pigs across video footage, with 92% multi-object tracking accuracy, and (iii) re-identify them, after occlusions and dropped frames, with 0.862 mean average precision.

Deep learning has shown a particular success when using 3D scanning. Sousa et al. (2018) built a sensor array consisting of a two-dimensional (2D) laser scanner and an encoder for the three-dimensional (3D) scanning of the back area of 107 Nellore cattle. The scanning data were taken in four periods, every 28 days, which allowed generating 304 clouds of points. They built an algorithm using delaunay and convex hull methods to obtain the height of the cattle's rump and the area of the rear view. They also built a neural model, with a multi-layered architecture. The input of the neural model was the rump height and rear view, and the output was an estimation of the live weight. Model performance was evaluated by comparing the estimated and measured weight of the cattle using linear-regression parameters. The coefficient of determination was 0.85 and the mean absolute percentage error was 4.57%, in previously unseen data.

In addition to machine learning, there is also research ondata visualization of the animal's well-being. Van Van Hertem et al. (2017) presented the development of a web-based tool for data visualization. Data was collected from five broiler farms and ten pig farms across Europe. At the farms, a number of variables were automatically measured including climate data, production data, environmental data, and data about animal behavior coming from cameras and microphones. Simultaneously, the health of the animals was assessed by trained assessors using a standardized health quality protocol. All data was gathered, stored and processed on a daily basis. End-users of the tool were trained on how to interpret the available information on the visualization tool.

Monitoring has also been applied to poultry farming. Stefanova (2017), Stefanova (2019) described the realization of a precision-livestock management-software that delivers monitoring and collaborative capabilities to improve laying hens health at industrial poultry farms. The online platform as a zoo-technical diary connects egg and breeding farms through cloud technologies to provide continuous data-recording, automatic comparisons between actual and expected production indicators, and integrated data-flow between the parties. According to Stefanova et al., breeding farms benefit from enhanced competitiveness, improved supplier-client relationships, while egg farms enjoy management precision, timely feedback on animals' health and economic benefits.

In the last work on general monitoring, Makinde et al. (2019) discussed the opportunities to apply research and methodologies emerging from *animal-computer interaction (ACI)* to help improve the usability and overall utility of PLF technologies for both, human and animal users.

Heat Monitoring. Heat stress affects animal health and productivity. In one work, Liu et al. (2018) developed a method for turkey-sound analysis and determine whether heat stress can induce specific turkey vocalizations. Forty-eight turkeys were bred in eight isolated rooms, under laboratory conditions, for eight weeks, and –randomly– allotted to heat-stress rooms and control rooms. SVM was used as the classifier for sound-signal recognition. The accuracy of classification was 88.75%. They demonstrated the possibility of using turkey vocal sound monitoring and analysis as an early warning tool for heat-stress detection. In another work, Milan et al. (2019) determined optimum supplemental heat requirements (supplied by heating lamps), for piglets, based on energy balance as a function of air temperature and animal body weight. They also defined the zone of least thermo-regulation of piglets, for a given weight, when supplemental heat is not provided. Energy balance was calculated using an ensemble of mechanistic models of bio-heat transfer that predicts hair-coat temperature, skin temperature, and skin-heat flux. Input temperatures were predicted from measured air temperature in the pen and supplemental heat using machine learning techniques. Predicted optimum supplemental heat showed an exponential-decay trend with increasing air temperature and/or animal weight.

Insemination Monitoring. Labrecque and Rivest (2018) proposed a novel approach to determine an optimal timing for insemination in sows, based on behavior analysis in real-time. Real-time analysis allows finding the statistically-optimal timing for insemination based on behavior-pattern recognition. The system was used for 21 months, in seven commercial farms, for 20,485 weaned sows. When used as a complement to a daily heat detection, the system allowed to easily manage 99.78% of the sows.

Lameness monitoring. Lameness indicates that something is wrong with the cattle. An approach to detect lameness is to use a sensor to track leg movement. Zhao et al. (2018) analyzed leg swing using computer-vision techniques, and developed an automatic and continuous system for scoring the locomotion of cows to detect and predict lameness with high accuracy. The focus was the quantification of the movement pattern of cows and the demonstration of the possibility of classifying lameness, using the features extracted from movement analysis. Side-view videos were recorded after the cows were milked. Cows were scored by an expert on a scale from 1 (healthy) to 3 (severely lame). The data set included 621 videos from 98 cows. The motion curve was plotted by extracting the position of the moving leg by image processing, and the motion curve was analyzed to generate six features referring to the gait asymmetry, speed, tracking up, stance time, stride length, and tenderness. The DT classifier was applied to the data set, and 2-, 3-, and 10-fold cross-validation was used to verify the performance of the algorithm. The accuracy of the classification was 90.18%, and the average sensitivity and specificity were 90.25% and 94.74%, respectively.

Another approach to detect lameness is to use *quantile regression forests (QRT)* instead of DT. Diez-Olivan et al. (2019) created a decision-support system based on environmental indicators, and on the weights, leg problems and mortality rates. The data-driven modeling process is performed by the QRT approach that allows estimating growth, health and mortality parameters on the basis of environmental deviations from optimal farm conditions.

Respiratory problems. The following works study respiratory diseases for growing pigs. Cowton et al. (2018) designed and evaluated a deep-learning-based methodology for animal-health monitoring. The methodology is, specifically, for the early detection of respiratory disease, in growing pigs, based on environmental sensor data. Two *recurrent neural networks (RNNs)* were used to create an *autoencoder (GRU-AE)*. The models received environmental data, collected from a variety of sensors, to detect anomalies. Cowton et al. used *Particle Swarm Optimization (PSO)* to raise alerts. The results showed that a change in the environment can result in pigs showing symptoms of respiratory disease within 1–7 days, meaning that there is a period of time during which their keepers can act to mitigate the negative effect of respiratory diseases, such as *porcine reproductive and respiratory syndrome (PRRS)*, a common and destructive disease endemic in pigs.

Health status. *FAffa MAlan CHArt (FAMACHA)* is a scoring system for detecting levels of anemia caused by parasite infection in small ruminants. FAMACHA is an effective way to identify individuals needing treatment. Montout et al. (2020) used training/test data sets, using FAMACHA scores, to construct a SVM classifier, to predict individuals that needed treatment.

4. Discussion

In this section, a summary of the revisions, the limitations of the reviewed works, and challenges for future works are presented.

4.1. Review summary

In this review, we have found that grazing, using ML techniques, in recent years, has focused –mainly– on sheep (40%) and cattle (60%). The most commonly used ML techniques for grazing are classification techniques. Most works on grazing have focused on obtaining, analyzing and understanding animal variables. With respect to animal health, a recent work has focused on how to improve animal production by controlling their health. Research has shown that estimating food consumption and monitoring feeding behavior are key activities to assess the health of animals. Also, most research on animal health has focused on understanding animal behavior. Nonetheless, both animal monitoring and animal behavior are complementary and needed to measure animal health and have not been considered together.

Fig. 5 summarizes all 35 studies, examining the problem they addressed, the proposed solution, and the tools and techniques used with the best performance.

Fig. 6 shows that the most commonly used ML techniques are SVM and DT. There are some possible explanations. For example, SVM has had great acceptance because it has the ability to discriminate data of different kinds by the means of kernels: The theoretical basis of kernels used in SVM makes it an exceptional tool for generalization in complex problems (Lemaire et al., 2018). On the other hand, DT predicts the value of a target variable by learning simple decision rules inferred from the characteristics of the data: This makes it easy to understand and interpret, requires little data preparation, and it is a white box model.

Fig. 7 shows the different sensors used in PLF. This figure shows the interest of the scientific community: In the first place, accelerometers and, in the second place, collar sensors. The third most used sensor is the video capture.

Accelerometers have been used in cattle to evaluate the activity patterns of dairy cattle (de Passillé et al., 2010), the resting behavior of calves (Bonk et al., 2013), and the analysis of the grazing vs. non-grazing in dairy cows (Nielsen, 2013). Accelerometers can be worn on a collar located on specific parts of the animal's body. A collar is a very important instrument because it can have all kinds of sensors, which are in charge of collecting the data and sending data, such as the GPS sensor. Video capture is the easiest way to monitor animals. By installing the cameras, it is possible to obtain data about what is happening to the animal and its environment in a non-invasive way.

4.2. Limitations of reviewed works

In this section, the limitations of ML for grazing and animal health in PLF are presented.

Machine Learning for Grazing in PLF. Management of pastures allows maintaining production levels in terms of forage produced per hectare, and milk and meat production per hectare. Therefore, analyzing and preparing the soil where the pasture will be established will give a good pasture management. In addition, a good pasture allows extensive livestock to obtain their food from grazing. In exchange, livestock fertilizes the land and facilitates soil tillage, demonstrating the complementary relationship between livestock and pasture agriculture (Lemaire et al., 2018).

In spite of the well-known importance of management of pastures, ML for grazing has focused, mostly, on classical classification techniques to understand the behavior of the animal. The use of these variables is centered on the animal; however, variables such as forage digestibility and animal production are not being used. Even worse, previous works have not taken into account soil variables, which, together with the animal activity, could lead to the creation of robust models to improve grazing methods, and, as a consequence, to a higher economical production. Finally, there are no works using unsupervised learning, or new ML techniques, such as semi-supervised learning (Cerrada et al., 2019), inherited learning (Salakhutdinov et al., 2012; Puerto and Aguilar, 2016) and meta-learning (Finn et al., 2017).

Machine Learning for Animal health in PLF. On ML for animal

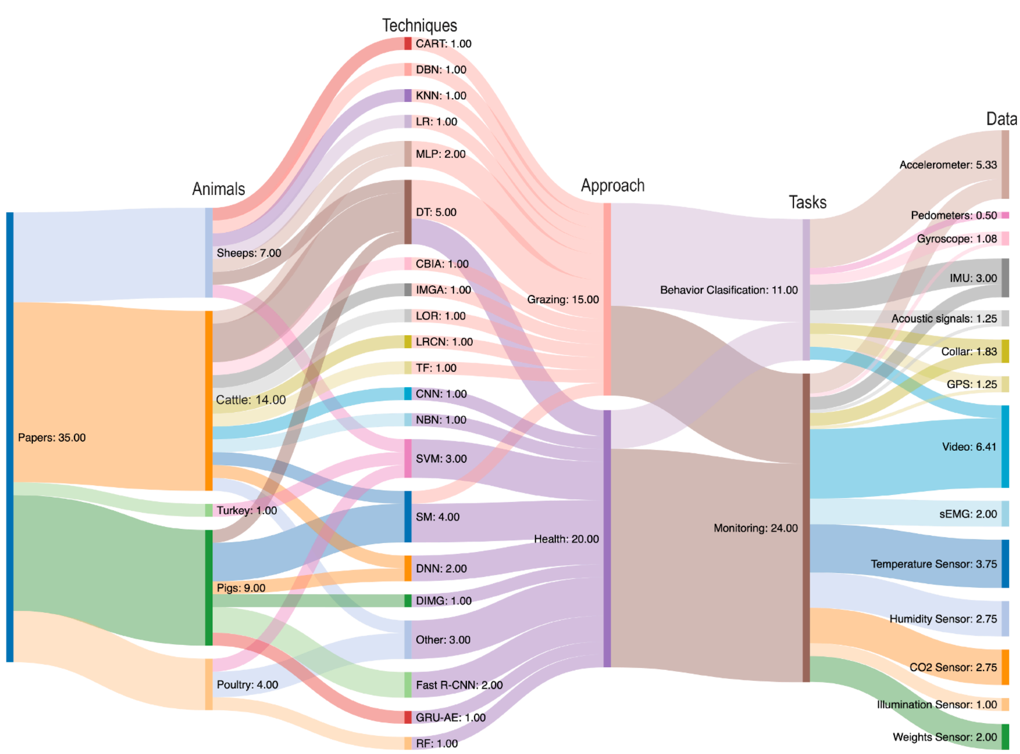

Fig. 5. Trends of reviewed documents.

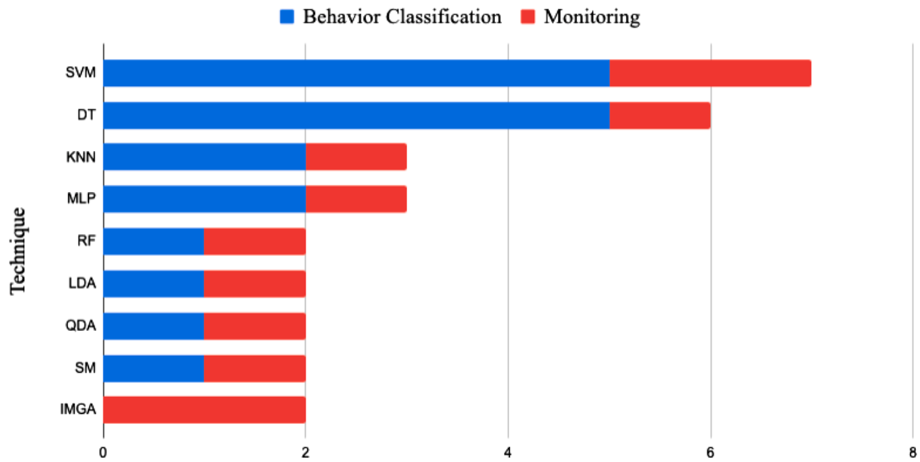

Fig. 6. Most used ML techniques in PLF.

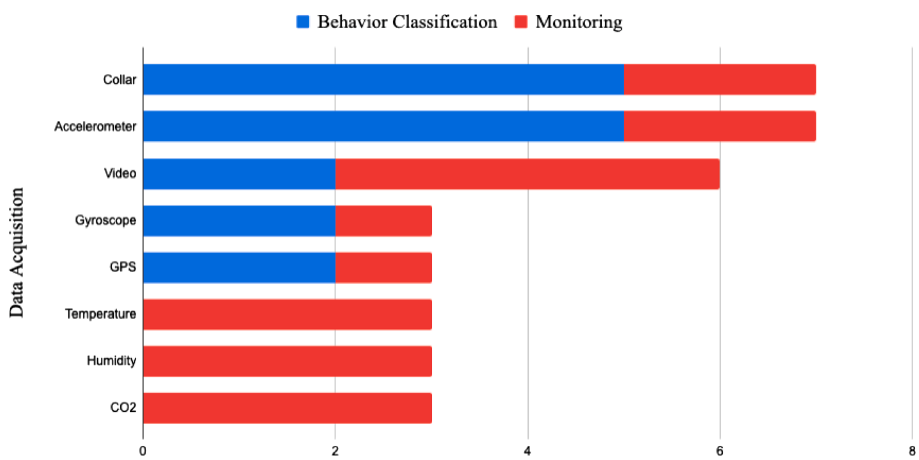

Fig. 7. Most used data-acquisition technologies in PLF.

health, the works have been centered on monitoring the animal and, also, on classic ML techniques for classification. There are no works where the degree of animal comfort under its environment is analyzed, except two on thermal comfort. There are no works of ML for diagnosis of diseases, prediction or prescription of treatments, except for two works on the diagnosis of lameness. Neither there are works in which one brings together data of animal health with the state of water drinkers. Dirty water can contain unhealthy bacteria for animals, and, eventually, dirty water could contribute to the reduction of production.

4.3. Challenges

Challenges for future works can be, broadly, classified into three categories: Machine learning, sensors and data sources, and data management. In what follows, each category of challenges is presented.

Machine learning. There is no evidence that grazing and animal health have been brought together in a ML model; therefore, trying to combine these aspects results in an interesting challenge. Bringing together grazing and animal health will also allow developing models of diagnosis and prescription as tools for the prevention and control of animal diseases. Such tools will entail considerable benefits to livestock production, food safety, public health, animal health and access to international markets.

To bring together grazing and animal health issues, a recommendation is the implementation of federated learning (Yang et al., 2019; Li et al., 2020). A federated ML model, for grazing and animal health, will allow data sets from different farms to be interconnected so that ML models work together, and they can be adapted to changing environments and event trends. Finally, to give autonomy to PLF, it is necessary to explore concepts such as *autonomous cycles of data analysis tasks* that consider all ML tasks working together (Aguilar et al., 2018b; Aguilar et al., 2018a), and often include meta-learning (Finn et al., 2017). This last challenge can be extended with concepts from the area of multi-agent systems (Aguilar et al., 2007), which allow modeling the entire PLF context in a natural way.

Another challenge in ML is about how to improve the classification performance of the algorithms used in PLF. Williams et al. (2019) determined that ensemble algorithms are very promising in PLF, but more work is needed to explore different strategies available, in the literature, for PLF tasks. Such PLF tasks can benefit from the added power of ensemble learning, which is already successful in other areas. As a final recommendation, many tasks can be treated not only as a classification problem, but also as a semi-supervised or a meta-learning problem.

Sensors and data sources. Systems based on sensor technologies are called upon to provide decisive information on conditions influencing livestock; for instance, to measure humidity, temperature, wind, rain, soil quality and animal health status. The use of sensors and data analysis focusing on real farm problems will ensure that farms are environmentally sustainable, and avoid wastes that have a major impact on soil contamination. The increasing availability of large data sources and data sets will encourage more initiatives, projects and new ventures in the livestock sector.

To improve ML for grazing, there are three key factors for pasture management: the frequency, intensity and duration of grazing. Nonetheless, these variables are not being taken into account. According to Arcos et al. (2019), considering such variables would help to correctly define the condition of the pasture, before and after grazing, so that grazing takes place at the right time and with the right intensity (Bell et al., 2014).

In ML for animal health, previous works have focused on pigs (31%), sheep (8%), poultry (38%) and beef (23%), and have a greater focus on animal monitoring with 75%, and behavioral classification with 25%. On animal health and environmental measurement sensors, the most used sensors are temperature, humidity, and CO_2 sensors. Van Hertem et al. (2017) proposed new sensors for the detection of early-signs of deviations in animal health, with low financial and energy costs. A challenge, in addition to the development of sensors, is how to determine the relevant signals: This is a problem of feature engineering.

Data management. There are some challenges related to data management in PLF. Stefanova (2019) proposed that most farm data is found in notebooks or in zoo-technical information systems. A challenge is the automatic digitization of all the useful data of a farm for the context of PLF.

Once farmers achieve automatic digitization, there is a challenge on how to make the system more energy efficient. To improve energy-saving, farmers have to merge data from different sources, reduce dimensions, minimize energy consumption in on-farm equipment, and compress data. In fact, Debauche et al. (2019) concluded that the use of data-compression algorithms can optimize battery-power consumption in the context of PLF. Another issue to save energy in PLF is how to minimize the amount of data transmitted to the cloud, as proposed by Doulgerakis et al. (2019). Doulgerakis et al. also proposed to apply intelligent energy-saving algorithms to optimize battery life.

A final challenge in data management is the following: Van Hertem et al. (2017) determined that the main barrier among farmers living in rural areas is the appropriate data visualization. For this reason, Van Hermet et al. concluded that a user-friendly interface, for the correct presentation of data, is a major challenge.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compag.2020.105826.

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