The Use of Machine Learning and Big Data in Predicting Diseases in Farm Animals and to Improve Animal Products

Goddeti. Mallikarjun
Assistant professor
Department of CSE
St. Martin's engineering college
Corresponding Author's E-mail: *goddeti.mallikarjun@gmail.com*

Abstract

Ever since man began domesticating creatures several thousand times agony, we've always reckoned on our suspicion, collaborative knowledge, and sensitive signals to make effective beast product opinions. So far, this has helped us make significant earnings in beast husbandry and husbandry. Together the growing demand for food and the advancement in seeing technology have the eventuality to make beast husbandry more centralized, large scale and effective. It has the implicit to change beast husbandry as we know it. At a broader position, this paper explores the challenges and openings that detector technologies present in terms of helping beast growers produce further meat and beast products. More specifically, this paper explores the part of detectors, big data, artificial intelligence and machine literacy in helping beast growers to lower product costs, increase edge, enhance beast weal and grow more creatures per hectare. It also explores the challenges and limitations of technology. The paper reviews colourful beast husbandry technology operations to understand its value in helping growers ameliorate beast health, increase gains and lower environmental footmark.

Keywords: *Machine Learning, Big Data, Collaborative Knowledge, Environmental Footmark, Beast Husbandry Technology Operations*

INTRODUCTION

1. Fewer Farms, More Animals

Historically, beast husbandry has always been decentralized, on a scale that a many individualities can get together and manage. And until a decade agone, utmost beast growers didn't have access to ultramodern technologies similar as high-speed internet, smart phones and cheap computing power. Now, both these conditions are changing snappily.

First, global demand for colourful meat and beast products is set to increase by over 70 in the coming three decades. We now know that encyclopaedically, wherever populations and inflows have risen, meat consumption has also increased. This means that we now need to produce further creatures with a limited quantum of land, water, and other natural coffers. Secondly, moment, further than half the global population is connected to the internet either through smart phones or computers. Cheap phones that can be carried in our pockets now have lesser calculation power than the computers on Apollo 11, the first manned spacecraft to land on moon. This means that calculating power is now fluently accessible by millions of beast growers.

It's estimated that growers need to increase product by 70 over the coming 50 times to meet the growing global demands of meat and beast products. Since land and other natural coffers are limited, to meet this growing demand we will need to find more effective ways of growing more creatures per hectare. This also means that homemade processes of beast husbandry may no longer be sufficient. It also means that we need to find ways and systems that help us achieve lesser earnings in beast husbandry.

Today, technologies such as computers, sensors, cloud computing, machine learning (ML) and artificial intelligence (AI) are already transforming several industries. They create greater gains and efficiencies. This is why we need to explore how these advanced technologies can help us achieve greater efficiencies and gains in animal farming.

2. Key Cost Drivers In Animal Farming

The number one value driving force in animal farming is stocking rate, described because the variety of animals grazing (sustaining) on a given quantity of land for a targeted time. In addition to this, as any farmer will inform you, the 2 primary prices in animal farming are feed and sickness management. Due to economies of scale, farmers can optimize their primary prices and decrease their manufacturing prices via way of means of growing the variety of animals they inventory in a system [3]. However, maximum animal farming practices these days want guide interventions at a few level. People verify feed rates, perceive and deal with sicknesses and cope with manufacturing. This locations limit on what number of animals may be cared for. Theoretically, if fewer humans can cope with many extra animals, this may dispose of the most important bottleneck in growing manufacturing in addition to profits.

3. Mechanistic Models, Sensors, Big Data & Advanced Algorithms

We use mechanistic models to elucidate causality in complex systems. A mechanistic model must be able to provide an explanation for the models of a system under study. This approach is very useful for solving complex problems involving several variables. Often times, this means that the problem cannot be solved by experimentation alone. Instead, solving such a complex problem requires the systematic collection and analysis of large volumes of data. In breeding, mechanistic models have the potential to solve complex problems such as: identification of functional limiting factors, determination of the optimal nutritional composition of feed, evaluation of animal management to assess performance [4], examining strategies to reduce "the excretion of nutrients into the environment [5] or to predict the results enters completely new scenarios [4]. To apply mechanistic models to animal husbandry, we need to collect a large volume of different data sets. Some of them may include local weather data, air quality data and animal signals, visual data of various animal movements, and other similar animal behaviour data.

Various sensors can help us effectively capture data in real time. But, as you can see, such a system will have to store large volumes of text, audio and video data. The storage and processing of these large amounts of data, every day, through the year is not possible with an ordinary computer. Big data plays a key role in applying advanced technologies to animal farming practices and offers a scalable solution to store vast amounts of data on a remote server.

Advanced AI and ML algorithms can make use of this extensive data to analyse, predict and notify farmers in case there is something abnormal (Fig. 1). Therefore, in the context of animal farming, sensors, big data, and advanced AI & ML algorithms go hand in hand to provide a complete solution. Often, through this paper we refer to this collection of technologies as 'advanced technologies'.

SCOPE AND LIMITATIONS

1. Finding Ways To Optimize Performance

In practice, these advanced technologies can be used to determine optimal solutions to many breeding problems. Some examples include finding optimal solutions to minimize costs, maximize production, increase efficiency, and create optimal dietary formulations [4]. Advanced models can also take into account variables such as genetics, environment and management priorities in order to find relevant and contextually optimal solutions. a solution will also have the benefit of providing farmers with an evidence-based or data-based solution.

2. Understanding Complex Systems

Advanced technologies now offer us the opportunity to explore the workings of complex systems such as biological systems. They can help us extract meaningful information from data and increase our ability to understand complex animal systems [6]. They can help us to compile experimental data and derive meaningful data parameters, for example, by deriving fractional rates of rumen degradation [7] or net rates of mammary cell proliferation [8]. Cutting edge technologies are not without failure, however. Indeed, they are exceptional tools for determining areas where scientific knowledge is insufficient, or where a hypothesis on the regulation of a system may be wrong [6]. The inability to mimic reality is good in some ways, as it has brought to light an area that has not been properly described, may have false assumptions, or in some cases even lack appropriate data. So, regardless of its ability to produce positive results or not, the application of advanced technologies to animal husbandry will help you gain more knowledge and ultimately advance our understanding of how animal systems work.

3. Recognizing Complex Patterns

Broadly, advanced technologies excel at interpreting various types of data such as text, audio, videos and images. Advanced algorithms can then cluster, classify or predict patterns within such datasets. Within animal production systems, pattern recognition through advanced data analysis and algorithms has been applied to the detection of disease and the monitoring of animals [6].

For example, a range of sensors along with big data and ML models have been developed to evaluate changes in animal behaviour (which may imply or represent a change in the heat, injury, metabolic state or the health status) or are used for animal identification [6]. We now have various sensors to classify animal behaviour such as resting, grazing and walking. Publications show how 3-axis accelerometers and magnetometers [9], optical sensors [10] or depth video cameras [11], along with ML models can help us classify and predict animal behaviour.

In addition to this, we also have additional examples of how big data and ML can help detect animal diseases earlier than conventionally possible. For example, Sadeghi et al. [12] recorded broiler vocalizations in healthy and Clostridium infected birds. The researchers identified and analysed five clusters of data using an Artificial Neural Network (ANN) model, which showed the distinction between infected and healthy birds and were able to discriminate between infected and healthy birds with an accuracy of 66.6% on day 2 and 100% on day 8 after infection. Similarly, infection may lead to discernible differences in movement patterns [13] and the surface temperature of animals [14], leading to earlier diagnosis or even prediction of disease out- breaks.

4. Predictive Abilities

This leads us to the ability of advanced technologies to forecast and predict outcomes of economic importance such as body weight (BW), milk yield or egg production. For example, Alonso et al. [15] used a support vector machine classification model to successfully predict the BW of individual cattle in cases where the past evolution of the herd BW is known. This approach surpassed individual regressions created for individual animals when there were only a small number of BW measure available and when precise predictions for longer durations were required.

Similarly, Pomar and Remus [5], Parsons et al. [16] as well as White et al. [17] have all proposed the use of machine vision based visual image analysis platforms to monitor BW in growing pigs from which they could evaluate appropriate feed allocations. Such predictive abilities have the potential to create new efficiencies and achieve greater animal farming gains.

IDENTIFYING, PREDICTING & PREVENTING DISEASES USING SENSORS

As mentioned earlier, identifying, predicting and stopping animal illnesses is a massive value driver. Typically, farmers tackle illnesses in their animals by way of both taking no action, pro-actively the usage of veterinary doc- tors, the use of a combine of antibiotics or in many instances by means of taking a aggregate of these three approaches.

Modern applied sciences such as sensors, massive data, AI and ML existing a new opportunity to farmers. Instead of reacting to ailments after they grow to be evident or pro-actively the use of the offerings of doctors, it affords an possibility to continuously display key animal fitness parameters such as movement, air quality, and consumption of meals and fluids. By continuously gathering this facts and the use of superior AI and ML algorithms to predict deviations or abnormalities, farmers can now identify, predict and forestall sickness outbreaks, even earlier than a large-scale out- break. In different words, sensors can continuously display animal fitness as an alternative of humans. Such a device has two main benefits. One, such a machine can allow fewer farmers to care for many greater animals, in flip reducing manufacturing costs. Two, such a device can notify farmers about the possibility of a disease, even throughout the pre-clinical stage. This will in flip assist farmers take well timed motion to forestall catastrophic losses [18].

A contagious sickness outbreak can purpose extreme losses in a giant animal farm, the place heaps of animals are sheltered together. In such a setting, the contagious sickness outbreak will be tough to comprise except the farmer takes well timed early interventions. Often it is already too late to intervene as soon as the signs and symptoms turn out to be evident. Left un- checked, a ailment will unfold hastily ensuing in a aggregate of animal deaths, poorer fitness consequences and economic losses [19]. On the different hand, a clever farm with quite a few sensors might also notify the farmer about strange animal behaviours at a whole lot previously stage.

1. **Sensors, Big Data & Machine Learning**

Automated structures excel at collecting, processing and analysing giant volumes of facts quickly. They can't make tremendous selections besides data. They can aid human beings in making higher choices when they gather and manner giant quantities of exhaustive data. Different sensors can assist farmer's song animal behaviours in real-time [20] on a farm. Advanced algorithms can make use of large information to track, quantify, and recognize animal behaviour changes. In turn, this can assist farmers make higher choices and function well timed disorder interventions [21, 22].

Today, there are a number of sensors accessible that can assist farmers tune adjustments in animal movements, meals intake, sleep cycles and even air satisfactory in animal shelters. The uncooked statistics is first saved and processed into a pc that is successful of managing large data. Finally, ML al-growths spotlight any variances or deviations from fashionable patterns. Sensors, massive statistics and ML algorithms have been employed to efficaciously diagnose the early onset of numerous illnesses that have an effect on pigs and sheep primarily based on torpid physique movements, slower response times, and reduced undertaking earlier than the onset of different sizeable sickness signs and symptoms [18, 19, and 23].

However, in a massive herd amongst quite a few animals, it is tough for farmers to spot these adjustments with the bare human eye. It is additionally equally challenging for a farmer or caretaker to spot adjustments in feeding habits, fluid consumption and uncommon physique actions of a ailing animal amongst a massive herd of animals. This is the place sensors, huge information and ML can play an integral function in assisting farmers turn out to be conscious of such strange behaviours, thereby rapidly predicting and stopping sickness outbreaks [24].

For example, air sensors in the fowl enterprise can now predict the onset of Coccidiosis [25], an intestinal contamination that can unfold shortly amongst birds besides any obvious symptoms. One way to perceive this disorder is by way of continuously monitoring air quality. Concentration of voletile natural compounds (VOC) in the air increase, as the wide variety of contaminated birds increase. Air sensors can become aware of this trade lots before than a farmer or physician could. The alerted farmers can then take well timed measures to forestall similarly unfold of the infection. Such a gadget saves countless animal lives and prevents monetary losses.

Similarly, amongst large animals, sensors, huge statistics and superior algorithms can predict countless ailments tons higher than people can ever hope to do. For instance, cows affected by using mastitis, an udder disease, quit up producing low exceptional and portions of milk. Conventionally, to diagnose mastitis, somatic phone counts (SSC) and electric powered conductivity (EC) readings are taken manually [26]. However, these guide readings can regularly flip out be unreliable, unsteady and no longer useful. Instead, automatic sensors and algorithms can now reliably collect predict and limit the threat of mastitis in cows [27].

IMPROVING ANIMAL HEALTH USING FACIAL RECOGNITION SYSTEMS

Identifying a precise animal amongst a herd or flock is an vital task. This is the first step in enhancing animal fitness results whilst managing corporations of farm animals, which has constantly been a challenge, in particular for giant scale animal farmers. Until recently, there have been no low cost and animal-friendly technological options to do this on a giant scale. RFID (Radio Frequency Identification) tags have been the closest solution. They had been low priced and they acquired the job done, however in a restricted way. RFID tags have their very own set of disadvantages.

First, the farmers had to pierce the tags into every animal's ears. This used to be each time-consuming for the farmer, as nicely as a painful technique for the animals. Second, analysing more than one RFID tags at the identical time was once problematic. This supposed that farmers may want to no longer get significant information when animals moved in a herd, as they frequently do. And finally, the expensive RFID readers mounted on farms have been susceptible to bodily damage. Over the previous few decades, facial consciousness in human beings has been an energetic lookup area.

Facial focus purposes have been used to enhance surveillance systems, discover threats, and create high-security get right of entry to systems. Recent developments in facial consciousness have been prolonged to perceive and understand numerous animal behaviour patterns [31]. Even in the past, analysing facial expressions of pigs [31], cattle [32–34] and sheep [35] confirmed promising results; however these beforehand facial attention structures that laboured primarily based on the Eigen faces technique, had sure limitations. For example, it should solely understand patterns with 77% accuracy [36]. This was once too lots of an error distinction to be beneficial for a massive farmer with a number of animals.

More recently, with good sized developments in hardware and software, we can now take in giant quantities of uncooked facts and rapidly flip them into meaningful results. Instead of one facial attention method, we can now rent three exceptional facial consciousness strategies such as the VGG-face mannequin [37], Fisher faces [38], and convolution neural networks. This non-invasive imaging machine acknowledges faces of character pigs, in a actual farm setting, with 96.7% accuracy. Such a machine now has the plausible to substitute the inefficient RFID tags completely, and assist farmers reveal their animals efficaciously [39] at scale. This in flip can assist farmers notably decrease their prices and labour requirements.

We are now coming into a technology the place these applied sciences are transferring from lookup labs into actual farms. For example, a cow-face detection device when coupled with the PANSNet-5 cognizance mannequin can now become aware of character cow faces with 98.3% accuracy [40]. These unique facial detection and attention fashions can now figure man or woman animal faces in complicated real-time scenarios, in the presence of some form deformation and even in situations the place there is inadequate records [41]. In addition to figuring out character animals, these facial awareness developments can additionally be prolonged to a number of different beneficial applications, such as supporting us study greater about the animal's emotional and attention state. For example, by means of reading the ear and eye actions of an animal, we can now interpret its temper and excitement degree with life like accuracy. Animals with eyes half-closed and backward-pointing ears showcase a comfortable state. On the different hand, greater excited or agitated animals will have a large component of seen sclera (the white of the eye) and forward-pointing ears [42].

We can now use technological know-how to apprehend achievable issues animals' face, besides surely being existing close to them. For example, if we locate that many cows are agitated in the feedlots, we may also conclude that there is something incorrect with the feeding stations. At least such a commentary needs similarly investigation. On some occasions, such investigations might also lead to insights that can be without difficulty ignored by means of humans, such as scarcity of feeding stations [42].

Or in any other case, it may assist us decide ache signs and symptoms in sheep. On in addition investigation, we may also discover injuries, illnesses or even proof of predator attacks. Tools such as SPFES (Sheep Pain Facial expression Scale) can now assist us reliably measure ache and pain in sheep [43]. Technology is getting higher at assisting farmers pinpoint troubles in real-time and attain extra insights about their animals. This in flip can lead to higher animal fitness and well-being effects [44].

GAINS IN OPTIMIZING FEED EFFICIENCY & ENERGY INTAKE

Feed charges can make up 40% to 60% of the whole fee on a dairy farm [45]. It is one of the largest prices of animal farming [46]. At the identical time, when animals do no longer get ample feed and fluids, productiveness takes a hit. Progressive farmers continually maintain a tab on this. Now, science can assist them do this greater accurately.

Feed and fluid intakes can differ a lot. Calving [47], warmth [48], and feed composition [49] can be massive elements that extend or decrease feed intake. For animals to get most fulfilling nutrition the feed should be balanced between cumbersome (low power and excessive volume) and pay attention (high power and low volume) feed [50]. Balanced feed ratios can assist improve animal metabolism.

To calculate feed efficiency, we want to take into account elements such as the quantity of feed intake, weight received by way of animals [46], and the place applicable, the quantity of milk and eggs produced. However, these elements are based totally on quite a few various and non-linear parameters that are tough to kind manually. RGB – D cameras can assist farmers measure feed consumption for character cows. In addition to this, quite a few superior algorithms such as TDIDT, ENET, SSD, ARIMA and CNNs can assist farmers assist farmers calibrate and optimize feed costs in accordance to their animal desires [46,49] (Table 2).

Technology can additionally assist us estimate overall performance of farm animals accurately. Their strength fees at some stage in lactation can be assessed primarily based on parity, milk yield components, and physique situation rating (BCS). Thus, metabolic popularity can be estimated the use of the accessible on-farm statistics of cows. As mentioned earlier, ML methods can assist farmers estimate milk yield, reproductive overall performance, calving time, breeding values, and even become aware of mastitis.

TOWARDS BETTER OUTCOMES

1. Lower Antibiotic Usage & Fodder Requirements

As discussed through this paper, sensors, big data and ML can significantly improve animal health and farmer outcomes. A lesser-known fact is that it can also help us transition towards a more humane and ecological farming future. It has immense potential to help us reduce fodder and antibiotic usage. In turn, this can lead to more significant carbon sequestration and lower antibiotic resistance. In addition to this, technology can help us better understand animal emotions.

2. Artificial Intelligence For Emotional Contagion

According to social psychology, the phrase ‘emotional contagion’ denotes the exercise of humans mimicking other people's emotions. In different cases, it can additionally denote the tendency of any individual to capture other's thoughts whilst dwelling at the equal vicinity [64]. Emotions, in animals, on the whole feature to assist them undertake a rapid response to deal correctly with their surroundings. It helps them together cross in the direction of something they desire or away from chance.

Furthermore, lookup suggests how altering the appreciation of an man or woman can alternate how they engage with their surroundings. Emotional conversation can be a beneficial device to adjust social interactions such as mating competition, play, maternal nursing, and crew defence. Harmonizing the emotional behaviours of character animals can assist different farm-animals increase extra empathy and different proper qualities. This may additionally end result in the whole herd growing sturdy social bonds and accelerated crew coordination.

We are going past the lookup on feelings and their influence on individuals. We are now commencing to learn about how emotional contagion and emotional expressions can beautify the well-being of whole agencies.

For instance, a variety of species use vocal alerts to exhibit exclusive emotional states. We have additionally observed that vocal indicators strongly correlate with emotional reactivity. Additionally, in a associated experiment, it was once discovered that home pigs exhibited behavioural and cardiac responses when they heard a misery name from some other pig. In a extra latest study, goats confirmed a head-orienting response to the proper aspect on every occasion they heard calls from different goats, indicating that they use components of their left hemisphere Genius actively to accomplice with non-threatening vocal alerts. These researches supply us sufficient clues into how essential vocal alerts and emotional states are interconnected.

ML-based AI can assist us become aware of the variables of emotional contagion primarily based on vocalizations, olfactory cues, etc. to realize the outburst of a precise sickness or stress. This has the plausible to assist us enhance the residing prerequisites and well-being of farm animal's significantly. While working with emotional contagion, equipment such as social community evaluation can be used to investigate the qualitative (e.g. agonistic) and quantitative (interaction count) records of social relations.

This can assist us higher predict any wonderful and terrible stimuli spreading amongst a crew, and in turn, can assist us keep away from terrible stimuli and feelings over time and promote a feel of well-being amongst farm animals.

Farmers. This is mainly genuine when it comes to predicting epidemic ailments in giant scale animal farms [18].

Machine Learning Algorithms Choice for Data Analysis

What and how many kinds of ML points are wished and which algorithms are therefore fantastic to handle the hassle of classification and the picks can figure out the favoured effect of the animal welfare evaluation. For example, from a set of forty four features, possibly solely 5 to seven facets can also be wanted to yield extraordinarily correct results. Hence, in real-time systems, massive function units may want to be challenging due to computational complexity and greater storage requirements.

In addition to electricity considerations, one of the key technical challenges for real-time and long-term farm animal behaviour monitoring is 'concept drifts'. Concept flow happens when a sensor platform and records evaluation gadget is required to adapt to a alternate in records distributions inside the concept.

In supervised classification problems, it is normally assumed that the fact in the sketch mannequin is randomly selected from the identical distribution as the factors that will be categorised in the future. This is an unrealistic assumption due to the dynamic nature of many unique classification problems. For example, when a machine is educated in one

CONCLUSIONS

The emergence of Agriculture four is fuelling the increase of adoption of sensing technologies, large data, and ML in present day animal farming. In the actuality of pandemic eventualities the place restrictions are making it challenging for veterinarians, nutritionists, and producers to go to the farms, barns, and feed mills; actual time 24/7 insights into the livestock's activity, consumption and manufacturing are needed. These insights enabled with the aid of the sensing applied sciences generate statistics which are accessed remotely ensuing in decrease value and greater overall performance responding to the needs of the consumer. Although AI and ML algorithms have developed so fast, there is a lack of standardization in the series and sharing of statistics globally.

However as greater farms get related to technology, AI and sensing applied sciences will begin enjoying a extra decisive position in supporting farmers see patterns and options to urgent issues in the current animal farming. While there are nevertheless numerous unknowns, limitations, and open-ended questions, one component is certain. In this decade, we will find out the proper electricity of human - synthetic talent collaborations in the farm animals sector.

REFERENCES

1. M.M. Rojas-Downing, A.P. Nejadhashemi, T. Harrigan, S.A. Woznicki, Climate change and livestock: impacts, adaptation, and mitigation, Clim. Risk Manag. 16 (2017)145–163, https://doi.org/10.1016/j.crm.2017.02.001.
2. S. Wolfert, L. Ge, C. Verdouw, M.J. Bogaardt, Big data in smart farming–a review, Agric. Syst. 153 (2017) 69–80, https://doi.org/10.1016/j.agsy.2017.01.023.
3. J.G. Stigler, The economies of scale, J. Law Econ. 1 (1958) 54–71.
4. N.S. Ferguson, Optimization: a paradigm change in nutrition and economic solutions, Adv. Pork Prod. 25 (2014) 121–127.
5. C. Pomar, A. Remus, Precision pig feeding: a breakthrough toward sustainability, Anim. Front. 9 (2) (2019) 52–

59,https://doi.org/10.1093/af/vfz006.

6. J.L. Ellis, M. Jacobs, J. Dijkstra, H. van Laar, J.P. Cant, D. Tulpan, N. Ferguson, et al., Animal (2020) 1–15, https://doi.org/10.1017/S1751731120000312.J. France, J. Dijkstra, M.S. Dhanoa, S. Lopez, A. Bannink, Estimating the extent of degradation of ruminant feeds from a description of their gas production profiles observed in vitro: derivation of models and other mathematical considerations, Br. J. Nutr. 83 (2) (2000) 143–150, https://doi.org/10.1017/S0007114500000180.
7. J. Dijkstra, J. France, M.S. Dhanoa, J.A. Maas, M.D. Hanigan, A.J. Roo D.E. Beever, A model to describe growth patterns of the mammary gland during pregnancy and lactation, J. Dairy Sci. 80 (10) (1997) 2340–2354, https://doi.org/10.3168/jds.S0022-0302(97)76185-X.
8. R. Dutta, D. Smith, R. Rawnsley, G. Bishop-Hurley, J. Hills, G. Timms, D. Henry, Dynamic cattle behavioural classification using supervised ensemble classifiers, Comput. Electron. Agric. 111 (2015) 18–28 https://doi.org/10.1016/j.compag.2014.12.002.
9. V. Pegorini, L. Zen Karam, C.S.R. Pitta, R. Cardoso, J.C.C. Da Silva, H.J. Kalinowski, R. Ribeiro, F.L. Bertotti, T.S. Assmann, In vivo pattern classification of ingestive behavior in ruminants using FBG sensors and machine learning, Sensors 15 (11) (2020) 28456–28471,https://doi.org/10.3390/s151128456.
10. S.G. Matthews, A.L. Miller, T. PlÖtz, I. Kyriazakis, Automated tracking to measure behavioural changes in pigs for health and welfare monitoring, Sci. Rep. 7 (1) (2017) 1–12 https://doi.org/10.1038/s41598-017-17451-6.
11. M. Sadeghi, A. Banakar, M. Khazaee, M.R. Soleimani, An intelligent procedure for the detection and classification of chickens infected by clostridium perfringens based on their vocalization, Braz. J. Poult. Sci. 17 (4) (2015) 537–544, https://doi.org/10.1590/1516-635X1704537-544.
12. F.M. Colles, R.J. Cain, T. Nickson, A.L. Smith, S.J. Roberts, M.C.J.

Maiden, D. Lunn, M.S. Dawkins, Monitoring chicken flock behaviour provides early warning of in- fection by human pathogen campylobacter, Proc. Biol. Sci. 283 (1822) (2016) 20152323, , https://doi.org/10.1098/rspb.2015.2323.

13. M.A. Jaddoa, A.A. Al-Jumeily, L.A. Gonzalez, H. Cuthbertson, Automatic tem- perature measurement for hot spots in face region of cattle using infrared thermography, Proc. Int. Conf. Informat. Contr. Autom. Robot. (2019) 29–31.
14. J. Alonso, A. Villa, A. Bahamonde, Improved estimation of bovine weight trajectories using support vector machine classification, Comput. Electron. Agric. 110 (2015) 36–41, https://doi.org/10.1016/j.compag.2014.10.001.
15. D.J. Parsons, D.M. Green, C.P. Schofield, C.T. Whittemore, Real-time control of pig growth through an integrated management system, Biosyst. Eng. 96 (2) (2007) 257–266,https://doi.org/10.1016/j.biosystemseng.2006.10.013.
16. R.P. White, C.P. Schofield, D.M. Green, D.J. Parsons, C.T. Whittemore, The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs, Anim. Sci. 78 (3) (2004) 409–418,https://doi.org/10. 1017/S1357729800058811.
17. K. Vander Waal, R.B. Morrison, C. Neuhauser, C. Vilalta, A.M. Perez, Translating big data into smart data for veterinary epidemiology, Front. Vet. Sci. 4 (2017) 110,https://doi.org/10.3389/fvets.2017.00110.
18. E. Fernández-Carrión, M. Martínez-Avilés, B. Ivorra, B. Martínez-López,
19. Á.M. Ramos, J.M. Sánchez-Vizcaíno, Motion-based video monitoring for early detection of livestock diseases: the case of African swine fever, PLoS One 12 (9)(2017),https://doi.org/10.1371/journal.pone.0183793. Nasirahmadi, B. Sturm, A.C. Olsson, K.H. Jeppsson, S. Müller, S. Edwards,
20. O. Hensel, Automatic scoring of lateral and sternal lying posture in grouped pigs using image processing and support vector machine, Comput. Electron. Agric. 156 (2019) 475–

481https://doi.org/10.1016/j.compag.2018.12.009.

21. L. Riaboff, S. Poggi, A. Madouasse, S. Couvreur, S. Aubin, N. Bédère, E. Goumand,Chauvin, G. Plantier, Development of a methodological framework for a robust Prediction of the main behaviours of dairy cows using a combination of machine learning algorithms on accelerometer data, Comput. Electron. Agric. 169 (2020) 105179,https://doi.org/10.1016/j.compag.2019.105179f.
22. B. Meunier, P. Pradel, K.H. Sloth, C. Cirié, E. Delval, M.M. Mialon, I. Veissier, Image analysis to refine measurements of dairy cow behaviour from a real-time location system, Biosyst. Eng. 173 (2018) 32–44, https://doi.org/10.1016/j.biosystemseng. 2017.08.019.
23. T. Van Hertem, E. Maltz, A. Antler, C.E.B. Romanini, S. Viazzi, C. Bahr, Schlageter-Tello, C. Lokhorst, D. Berckmans, I. Halachmi, Lameness detection based on multivariate continuous sensing of milk yield, rumination, and neck ac- tivity, J. Dairy Sci. 96 (7) (2013) 4286–4298, https://doi.org/10.3168/jds.2012-6188.
24. A.S. Dhoble, K.T. Ryan, P. Lahiri, M. Chen, X. Pang, F.C. Cardoso, K.D. Bhalerao, Cytometric fingerprinting and machine learning (CFML): a novel label-free, objec- tive method for routine mastitis screening, Comput. Electron. Agric. 162 (2019)505 513https://doi.org/10.1016/j.compag.2019.04.029.
25. F. Borgonovo, V. Ferrante, G. Grilli, R. Pascuzzo, S. Vantini, M. Guarino, A data- driven prediction method for an early warning of Coccidiosis in intensive livestock systems: a preliminary study, Animals. 10 (4) (2020) 747, https://doi.org/10.3390/ ani10040747.
26. M. Gertz, K. Große-Butenuth, W. Junge, B. Maassen-Francke, C. Renner, H. Sparenberg, J. Krieter, Using the XGBoost algorithm to classify neck and leg activity sensor data using on-farm health recordings for locomotor-associated diseases, Comput. Electron. Agric. 173 (2020) 105404, , https://doi.org/10.1016/j.compag.2020.105404.

27. A.Hidalgo, F. Zouari, H. Knijn, S. van der Beek, Prediction of postpartum diseases of dairy cattle using machine learning, Proc. World Congr. Genet. Appl. Livest.Prod. (2018) 104.
28. M. Taneja, J. Byabazaire, N. Jalodia, A. Davy, C. Olariu, P. Malone, Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle, Comput. Electron. Agric. 171 (2020) 105286,https://doi. org/10.1016/j.compag.2020.105286.
29. D. Warner, E. Vasseur, D.M. Lefebvre, R. LacroiX, A machine learning based deci- sion aid for lameness in dairy herds using farm-based records, Comput. Electron. Agric. 169 (2020) 105193, , https://doi.org/10.1016/j.compag.2019.105193.
30. M. Ebrahimi, M. Mohammadi-Dehcheshmeh, E. Ebrahimie, K.R. Petrovski, Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: deep learning and gradient-boosted trees outperform other models, Comput. Biol. Med. 114 (2019) 103456,https://doi.org/10.1016/j.compbiomed. 2019.103456.
31. P. Ahrendt, T. Gregersen, H. Karstoft, Development of a real-time computer vision system for tracking loose-housed pigs, Comput. Electron. Agric. 76 (2) (2011) 169–174, https://doi.org/10.1016/j.compag.2011.01.011.
32. S.M. Porto, C. Arcidiacono, U. Anguzza, G. Cascone, The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision- based system, Biosyst. Eng. 133 (2015) 46–55, https://doi.org/10.1016/j. biosystemseng.2015.02.012.
33. C. Arcidiacono, S.M.C. Porto, M. Mancino, G. Cascone, Development of a threshold- based classifier for real-time recognition of cow feeding and standing behavioural activities from accelerometer data, Comput. Electron. Agric. 134 (2017) 124–134, https://doi.org/10.1016/j.compag.2017.01.021.
34. S. Kumar, S.K. Singh, A.K. Singh, Muzzle point pattern based techniques for in- dividual cattle

identification, IET Image Process. 11 (10) (2017) 805–814, https:// doi.org/10.1049/iet-ipr.2016.0799.

35. U.G. Barron, G. Corkery, B. Barry, R. Butler, K. McDonnell, S. Ward, Assessment of retinal recognition technology as a biometric method for sheep identification, Comput. Electron. Agric. 60 (2) (2008) 156–166, https://doi.org/10.1016/j. compag.2007.07.010.
36. N. Wada, M. Shinya, M. Shiraishi, Pig face recognition using Eigenspace method, ITE Trans. Media Techn. Appl. 1 (4) (2013) 328–332.
37. O.M. Parkhi, A. Vedaldi, A. Zisserman, Deep Face Recognition, (2015).
38. P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, Eigenfaces vs. fisherfaces: re- cognition using class specific linear projection, Eur. Conf. Comput. Vis. 19 (7) (1996) 711–720.
39. M.F. Hansen, M.L. Smith, L.N. Smith, M.G. Salter, E.M. Baxter, M. Farish, B. Grieve, Towards on-farm pig face recognition using convolutional neural networks, Comput. Ind. 98 (2018) 145–152, https://doi.org/10.1016/j.compind.2018.02. 016.
40. C. Liu, B. Zoph, M. Neumann, J. Shlens, W. Hua, L. Li, L. Fei-Fei, A. Yuille, J. Huang, K. Murphy, Progressive neural architecture search, Eur. Conf. Comput. Vis. (2018) 19–34.
41. L. Yao, Z. Hu, C. Liu, H. Liu, Y. Kuang, Y. Gao, Cow face detection and recognition based on automatic feature extraction algorithm, Proc. ACM Turing Celebration Conf. China (2019) 1–5.
42. M. Battini, A. Agostini, S. Mattiello, Understanding cows' emotions on farm: are eye white and ear posture reliable indicators? Animals 9 (8) (2019) 477, https://doi.org/10.3390/ani9080477.
43. K.M. McLennan, C.J.B. Rebelo, M.J. Corke, M.A. Holmes, M.C. Leach, F. Constantino-Casas, Development of a facial expression scale using footrot and mastitis as models of pain in sheep, Appl. Anim. Behav. Sci. 176 (2016) 19–26,https://doi.org/10.1016/j.applanim.2016.01.007.
44. K. McLennan, M. Mahmoud, Development of an automated pain facial expression detection system for sheep (Ovis Aries), Animals 9 (4) (2019) 196, https://doi.org/ 10.3390/ani9040196.

45. D. Amaral-Phillips, What Does it Cost to Feed your Cows? https://afs.ca.uky.edu/ files/what_does_it_cost_you_to_fe ed_your_cows.pdf, (2020).
46. M. Piles, C. Fernandez-Lozano, M. Velasco-Galilea, O. González-Rodríguez, J.P. Sánchez, D. Torrallardona, M. Ballester, R. Quintanilla, Machine learning ap- plied to transcriptomic data to identify genes associated with feed efficiency in pigs, Genet. Sel. Evol. 51 (1) (2019) 10.
47. M.H. Ghaffari, A. Jahanbekam, H. Sadri, K. Schuh, G. Dusel, C. Prehn, J. Adamski, C. Koch, H. Sauerwein, Metabolomics meets machine learning: longitudinal meta- bolite profiling in serum of normal versus overconditioned cows and pathway analysis, J. Dairy Sci. 102 (12) (2019) 11561–11585, https://doi.org/10.3168/jds. 2019-17114.
48. M.T. Gorczyca, K.G. Gebremedhin, Ranking of environmental heat stressors for dairy cows using machine learning algorithms, Comput. Electron. Agric. 168 (2020) 105124, https://doi.org/10.1016/j.compag.2 019.105124.
49. S. Nikoloski, P. Murphy, D. Kocev, S. Džeroski, D.P. Wall, Using machine learning to estimate herbage production and nutrient uptake on Irish dairy farms, J. Dairy Sci. 102 (11) (2019) 10639–10656,https://doi.org/10.3168/jds.2 019-16575.