Sensing and Bio-Sensing Research 29 (2020) 100367

Contents lists available at ScienceDirect

Sensing and Bio-Sensing Research

journal homepage: www.elsevier.com/locate/sbsr

The role of sensors, big data and machine learning in modern animal farming

Suresh Neethirajan

Ajna Consulting, 42 Edwards Street, Guelph, ON N1E 0B3, Canada

ARTICLE INFO

Keywords:
Smart farming
Animal health
Well-being
Sensor systems
Precision livestock farming

ABSTRACT

Ever since man began domesticating animals several thousand years ago, we have always relied on our intuition, collective knowledge, and sensory signals to make effective animal production decisions. So far, this has helped us make significant gains in animal husbandry and farming. Together the growing demand for food and the advancement in sensing technology have the potential to make animal farming more centralized, large scale and efficient. It has the potential to change animal farming as we know it. At a broader level, this paper explores the challenges and opportunities that sensor technologies present in terms of helping animal farmers produce more meat and animal products. More specifically, this paper explores the role of sensors, big data, artificial intelligence and machine learning in helping animal farmers to lower production costs, increase efficiencies, enhance animal welfare and grow more animals per hectare. It also explores the challenges and limitations of technology. The paper reviews various animal farming technology applications to understand its value in helping farmers improve animal health, increase profits and lower environmental footprint.

1. Introduction

1.1. Fewer farms, more animals

Historically, animal farming has always been decentralized, on a scale that a few individuals can get together and manage. And until a decade ago, most animal farmers did not have access to modern technologies such as high-speed internet, smart phones and cheap computing power. Now, both these conditions are changing quickly.

First, global demand for various meat and animal products is set to increase by over 70% in the next three decades. We now know that globally, wherever populations and incomes have risen, meat consumption has also increased. This means that we now need to produce more animals with a limited amount of land, water, and other natural resources. Secondly, today, more than half the global population is connected to the internet either through smartphones or computers. Cheap phones that can be carried in our pockets, now have greater computation power than the computers on Apollo 11, the first manned spacecraft to land on moon. This means that computing power is now easily accessible by millions of animal farmers.

It is estimated that farmers need to increase production by 70% over the next 50 years to meet the growing global demands of meat and animal products [1]. Since land and other natural resources are limited, to meet this growing demand we will need to find more efficient ways of growing more animals per hectare. This also means that manual processes of animal farming may no longer be sufficient. It also means that we need to find ways and systems that help us achieve greater gains in animal farming.

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 [2]. This is why we need to explore how these advanced technologies can help us achieve greater efficiencies and gains in animal farming.

1.2. Key cost drivers in animal farming

The primary cost driver in animal farming is stocking rate, defined as the number of animals grazing (sustaining) on a given amount of land for a specified time. In addition to this, as any farmer will tell you, the two major costs in animal farming are feed and disease management. Due to economies of scale, farmers can optimize their major costs and lower their production costs by increasing the number of animals they stock in a system [3]. However, most animal farming practices today need manual interventions at some level. People assess feed rates, identify and treat diseases and take care of production. This places limits on how many animals can be cared for. Theoretically, if fewer people can take care of many more animals, this will remove the biggest bottleneck in increasing production as well as profits.

E-mail address: sneethir@gmail.com.

https://doi.org/10.1016/j.sbsr.2020.100367
Received 2 June 2020; Received in revised form 30 June 2020; Accepted 3 July 2020

1.3. Mechanistic models, sensors, big data & advanced algorithms

We use mechanistic models to elucidate causality in complex systems. A mechanistic model should be able to provide an explanation for the patterns of a system under study. This approach is most useful in solving complex problems that have several variables. Often this means the problem cannot be solved by mere experimentation alone. Instead, solving such a complex problem needs systematic collection and analysis of large volumes of data.

In animal farming, mechanistic models have the potential to solve complex problems such as: identifying functional limiting factors, determining optimal nutrient composition of animal feed, evaluating animal management to evaluate performance [4], examining strategies to reduce nutrient excretion into the environment [5] or forecasting outcomes in other completely new scenarios [4].

To apply mechanistic models in animal farming, we need to collect a large volume of diverse datasets. Some of them may include local weather data, air quality data, voice signals of animals, visual data of various animal movements and other such animal behavior data. Various sensors can help us capture real-time data effectively. But, as you can see, such a system will need to store large volumes of textual, audio and video data. Storing and processing such vast amounts of data, every day, through the year is not possible with an ordinary computer. It will soon run out of storage and computing power.

A sensor can be defined as a device which measures or detects a biological, chemical, physical or.

mechanical property or a combination of these properties, records and collects the data for interpretation by a human or a machine. Based on the animal farming market needs, the sensor technologies can be classified in to the types such as sensors for precision milking robots and feeding systems; application based on the species (poultry, ruminant, swine, other farm animals); Hardware sensors such as camera or vision sensors; infrared thermal imaging sensors; temperature sensor; RFID tags; accelerometer; motion sensors; pedometers; facial recognition machine vision sensors; microphones etc.; Functional Process such based on climate control; weight estimates; animal behavior; emotional contagion; feed dosage, water usage etc.; and wearable vs non-wearable sensors and invasive vs non-invasive sensors.

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 analyze, 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'.

2. Advanced technology and animal farming

2.1. Finding ways to optimize performance

In practice, these advanced technologies can be used to determine optimal solutions to many animal farming problems. A few examples include finding optimal solutions to minimize costs, maximize production, increase efficiencies and create optimal diet formulations [4].

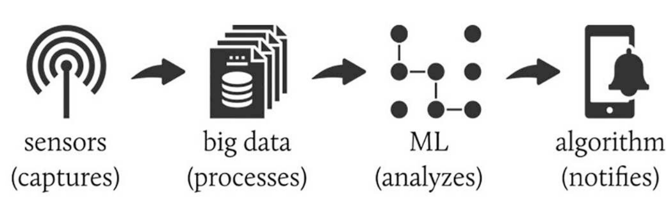

Fig. 1. The collection of technologies, that we refer to as advanced technologies, can help animal farmers create better outcomes.

Advanced models may even consider variables such as genetics, environment and management priorities in order to come up with relevant and contextually optimal solutions. In general, the more diverse datasets a system collects and analyzes, the better are its chances of arriving at accurate and optimal solutions [6]. Such a solution will also have the advantage of providing farmers an evidence-based or data-driven solution.

2.2. Understanding complex systems

Advanced technologies now provide us an opportunity to explore how complex systems such as biological systems work. It can help us extract meaningful information from data and increase our ability to understand complex animal systems [6]. They can help us compile experimental data and derive meaningful parameters, for example, deriving fractional rates of rumen degradation [7] or clear-cut rates of mammary cell proliferation [8].

However, advanced technologies are not exempt from failing. In fact, they are exceptional tools for determining areas where scientific knowledge is inadequate, or where an assumption on the regulation of a system may be incorrect [6]. Failure to mimic reality is good in a way because it has thrown light on an area that has either not been appropriately described, could have false assumptions, or in some cases even lack appropriate data. So, irrespective of its ability to provide successful outcomes or not, applying advanced technologies to animal farming will help us gain more knowledge and ultimately advance our understanding of how animal systems work.

2.3. 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 behavior (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 behavior such as resting, ruminating, 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 behavior.

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 perfringens* infected birds. The researchers identified and analyzed 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 outbreaks.

2.4. 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 measures 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.

3. Identifying, predicting & preventing diseases using sensors

As discussed earlier, identifying, predicting and preventing animal diseases is a big cost driver. Typically, farmers address diseases in their animals by either taking no action, pro-actively using veterinary doctors, using a mix of antibiotics or in many cases by taking a combination of these three approaches.

Modern technologies such as sensors, big data, AI and ML present a new possibility to farmers. Instead of reacting to diseases after they become evident or pro-actively using the services of doctors, it provides an opportunity to constantly monitor key animal health parameters such as movement, air quality, and consumption of food and fluids. By constantly collecting this data and using advanced AI and ML algorithms to predict deviations or abnormalities, farmers can now identify, predict and prevent disease outbreaks, even before a large-scale outbreak. In other words, sensors can constantly monitor animal health instead of humans. Such a system has two major benefits. One, such a system can enable fewer farmers to care for many more animals, in turn lowering production costs. Two, such a system can notify farmers about the possibility of a disease, even during the pre-clinical stage. This will in turn help farmers take timely action to prevent catastrophic losses [18].

A contagious disease outbreak can cause severe losses in a large animal farm, where thousands of animals are sheltered together. In such a setting, the contagious disease outbreak will be hard to contain unless the farmer takes timely early interventions. Often it is already too late to intervene once the symptoms become evident. Left unchecked, a disease will spread rapidly resulting in a combination of animal deaths, poorer health outcomes and financial losses [19]. On the other hand, a smart farm with several sensors may notify the farmer about abnormal animal behaviors at a much earlier stage.

3.1. Sensors, big data & machine learning

Automated systems excel at collecting, processing and analyzing large volumes of data quickly. They cannot make effective decisions without data. They can assist humans in making better decisions when they collect and process large amounts of exhaustive data. Different sensors can help farmers track animal behaviors in real-time [20] on a farm. Advanced algorithms can make use of big data to track, quantify, and understand animal behavior changes. In turn, this can help farmers make better decisions and perform timely disease interventions [21,22].

Today, there are several sensors available that can help farmers track changes in animal movements, food intake, sleep cycles and even air quality in animal shelters. The raw data is first stored and processed into a computer that is capable of handling big data. Finally, ML algorithms highlight any variances or deviations from standard patterns.

Sensors, big data and ML algorithms have been employed to successfully diagnose the early onset of several diseases that affect pigs and sheep based on lethargic body movements, slower response times, and decreased activity before the onset of other noticeable disease symptoms [18,19,23]. However, in a large herd among several animals, it is hard for farmers to spot these changes with the naked human eye.

It is also equally hard for a farmer or caretaker to spot changes in feeding habits, fluid intake and unusual body movements of a sick animal among a large herd of animals. This is where sensors, big data and ML can play an essential role in helping farmers become aware of such abnormal behaviors, thereby promptly predicting and preventing disease outbreaks [24].

For example, air sensors in the poultry industry can now predict the onset of Coccidiosis [25], an intestinal infection that can spread quickly among birds without any apparent symptoms. One way to identify this disease is by constantly monitoring air quality. Concentration of volatile organic compounds (VOC) in the air increase, as the number of infected birds increase. Air sensors can detect this change much earlier than a farmer or doctor could. The alerted farmers can then take timely measures to prevent further spread of the infection. Such a system saves several animal lives and prevents financial losses.

Similarly, among larger animals, sensors, big data and advanced algorithms can predict several diseases much better than humans can ever hope to do. For instance, cows affected by mastitis, an udder disease, end up producing low quality and quantities of milk. Conventionally, to diagnose mastitis, somatic cell counts (SSC) and electric conductivity (EC) readings are taken manually [26]. However, these manual readings can often turn out be unreliable, unsteady and not useful. Instead, automated sensors and algorithms can now reliably collect, predict and reduce the risk of mastitis in cows [27].

Early disease detection methods are nothing new. We already have technologies such as RtPCR to do this. However, they were costly and could not be adopted at scale. Today, sensors, big data and ML algorithms have a significant cost advantage over these older detection methods (Fig. 2). At a fraction of cost, they can quickly predict and prevent a contagious disease such as African Swine Flu [19]. More importantly, advanced technology can now predict many infectious diseases before they spread on a large scale (Table 1).

In other cases, algorithms can predict disease symptoms such as lameness based on animal movements. Changes in locomotion, extensive use of certain body parts and inactivity in other parts can reliably indicate early lameness at the preclinical stage [28]. Because lameness significantly reduces milk production and increases injury risk, it is the third most important disease that affects farming [29]. Predicting lameness in advance can help farmers avoid severe financial losses.

In yet another example, studies show that infected pigs move less, by up to 10% during the first two days of an infection. This can be used as a basis to isolate infected animals before they infect many more animals [19]. Finally, sensors collecting environmental data, such as

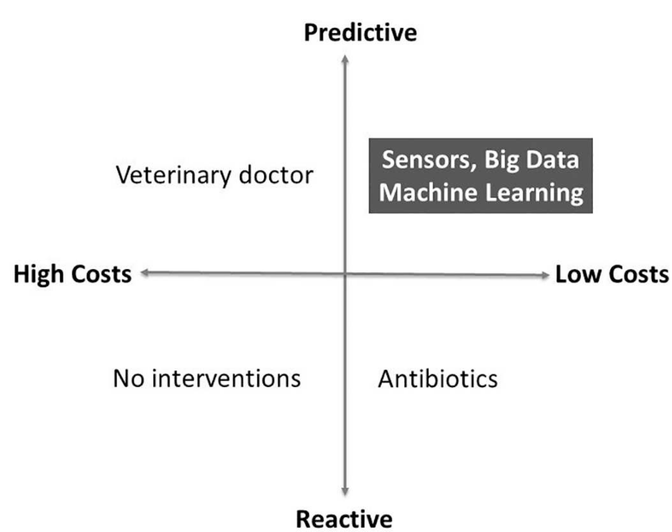

Fig. 2. Difference between predictive and reactive paradigms of managing diseases among animals.

Table 1
How advanced technology can help animal farmers predict & prevent diseases.

Disease	Algorithm(s)	Parameter detected	Paper
Mastitis	Bag of Words (BoW), Gradient Boosted Trees (GBT)	Somatic cell Count (SSC), Electrical Conductivity (EC)	[24,30]
Lameness	Fog computing, Classification and regressive tree (CART) XGBoost algorithm	Leg movement, Neck movement and Image/Video data	[26,28,29]
Postpartum disease	Random Forest Algorithm (RFA)	Lactose yield, Protein production, Milk yield	[27]
Coccidiosis	Principal Component Analysis (PCA)	Volatile Organic Compounds (VOC) in air	[25]
African Swine Flu	Optical flow algorithm	Mobility, speed, direction	[19]

changes in temperature, gas production, and humidity, can help farmers prevent diarrhea and bacterial diseases among pigs [25]. These examples showcase how sensors, big data and ML can help farmers predict and prevent several diseases in a cost-effective and non-invasive manner.

4. Improving animal health using facial recognition systems

Identifying a particular animal among a herd or flock is an important task. This is the first step in improving animal health outcomes while managing groups of farm animals, which has always been a challenge, especially for large scale animal farmers. Until recently, there were no cost-effective and animal-friendly technological solutions to do this on a large scale. RFID (Radio Frequency Identification) tags were the closest solution. They were cheap and they got the job done, but in a limited way. RFID tags have their own set of disadvantages.

First, the farmers had to pierce the tags into each animal's ears. This was both time-consuming for the farmer, as well as a painful process for the animals. Second, reading multiple RFID tags at the same time was problematic. This meant that farmers could not get meaningful data when animals moved in a herd, as they often do. And finally, the expensive RFID readers installed on farms were prone to physical damage.

Over the past few decades, facial recognition in humans has been an active research area. Facial recognition applications have been used to improve surveillance systems, identify threats, and create high-security access systems. Recent advancements in facial recognition have been extended to identify and recognize several animal behavior patterns [31].

Even in the past, studying facial expressions of pigs [31], cattle [32–34] and sheep [35] showed promising results, but these earlier facial recognition systems that worked based on the Eigenfaces technique, had certain limitations. For example, it could only recognize patterns with 77% accuracy [36]. This was too much of an error difference to be useful for a large farmer with several animals.

More recently, with significant advancements in hardware and software, we can now take in large amounts of raw data and quickly turn them into meaningful results. Instead of one facial recognition method, we can now employ three different facial recognition methods such as the VGG-face model [37], Fisherfaces [38], and convolutional neural networks. This non-invasive imaging system recognizes faces of individual pigs, in a real farm setting, with 96.7% accuracy. Such a system now has the potential to replace the inefficient RFID tags completely, and help farmers monitor their animals efficiently [39] at scale. This in turn can help farmers significantly reduce their costs and labor requirements.

We are now entering an era where these technologies are moving from research labs into real farms. For example, a cow-face detection system when coupled with the PANSNet-5 recognition model can now detect individual cow faces with 98.3% accuracy [40]. These different facial detection and recognition models can now discern individual animal faces in complex real-time scenarios, in the presence of some shape deformation and even in instances where there is insufficient data [41]. In addition to identifying individual animals, these facial recognition advancements can also be extended to several other useful applications, such as helping us learn more about the animal's emotional and attentional state. For example, by studying the ear and eye movements of an animal, we can now interpret its mood and excitement level with reasonable accuracy. Animals with eyes half-closed and backward-pointing ears exhibit a relaxed state. On the other hand, more excited or agitated animals will have a larger portion of visible sclera (the white of the eye) and forward-pointing ears [42].

We can now use technology to understand potential problems animals face, without actually being present near them. For example, if we find that many cows are agitated in the feedlots, we may conclude that there is something wrong with the feeding stations. At least such an observation demands further investigation. On some occasions, such investigations may lead to insights that can be easily missed by humans, such as shortage of feeding stations [42].

Or in another case, it might help us determine pain symptoms in sheep. On further investigation, we may find injuries, diseases or even evidence of predator attacks. Tools such as SPFES (Sheep Pain Facial Expression Scale) can now help us reliably measure pain and discomfort in sheep [43]. Technology is getting better at helping farmers pinpoint problems in real-time and gain more insights about their animals. This in turn can lead to better animal health and well-being outcomes [44].

5. Gains in optimizing feed efficiency & energy intake

Feed costs can make up 40% to 60% of the total expense on a dairy farm [45]. It is one of the biggest expenses of animal farming [46]. At the same time, when animals do not get adequate feed and fluids, productivity takes a hit. Progressive farmers always keep a tab on this. Now, technology can help them do this more accurately.

Feed and fluid intakes can vary a lot. Calving [47], heat [48], and feed composition [49] can be significant factors that increase or decrease feed intake. For animals to get optimal nutrition, the feed must be balanced between bulky (low energy and high volume) and concentrate (high energy and low volume) feed [50]. Balanced feed ratios can help boost animal metabolism.

To calculate feed efficiency, we need to take into account factors such as the amount of feed intake, weight gained by animals [46], and where applicable, the amount of milk and eggs produced. However, these factors are based on several diverse and non-linear parameters that are difficult to sort manually. RGB – D cameras can help farmers measure feed intake for individual cows [51]. In addition to this, several advanced algorithms such as TDIDT, ENET, SSD, ARIMA and CNNs can help farmers help farmers calibrate and optimize feed expenses according to their animal needs [46,49–52] (Table 2).

Technology can also help us estimate performance of farm animals accurately [53]. Their energy expenditures during lactation can be assessed based on parity, milk yield components, and body condition score (BCS). Thus, metabolic status can be estimated using the available on-farm data of cows. As discussed earlier, ML techniques can help farmers estimate milk yield [54], reproductive performance [55], calving time [56], breeding values [53], and even detect mastitis [57,58] (Fig. 3).

There are also several other applications of sensors, like helping us track behavioral changes to identify cows that are going through estrous [21], and cows that have effective digestive activity [49]. This will help farmers produce high quality milk [51,59] and in turn help

Table 2
How advanced algorithms collect data to help farmers monitor the feed intake vs the efficiency of the feed.

Algorithms	Data collection method	Reference
Top-down induction of decision trees (TDIDT) algorithm	Weight and concentration of food, Drones and manual entries	[49]
Random Forest Algorithm elastic net (ENET) and nearest shrunken centroid algorithm	Metabolic rate, Gene expression, Average daily weight gain, and Average Back fat gain	[46]
Sing Shot multi-box Detector (SSD) algorithm	Body Condition Score (BCS) through the multicamera system	[52]
Auto-Regressive Moving Average model (ARIMA)	Feeding weight of dry and concentrate and milk production by each cow	[50]
Convolutional Neural Networks (CNNs)	RGB camera, RFID for cow feed intake and milk production measurement and frequency	[51]

them earn better profits.

Acidosis in cows can also be detected by monitoring behaviors of animals through motion and sound sensors [60]. Similarly, calving time can be successfully predicted with more than 90% accuracy. This has the potential to replace other expensive, time-consuming, and often inaccurate alternatives. Predicting the exact time of calving also helps reduce delivery pain and dystocia. This is a huge step towards improved herd management [61].

6. Towards better outcomes

6.1. 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 [62] and lower antibiotic resistance [63]. In addition to this, technology can help us better understand animal emotions.

6.2. Artificial intelligence for emotional contagion

According to social psychology, the word 'emotional contagion' denotes the practice of people mimicking other people's emotions. In other cases, it can also denote the tendency of someone to catch other's emotions while living at the same place [64]. Emotions, in animals, mainly function to help them adopt a quick response to deal efficiently with their surroundings. It helps them collectively move towards something they want or away from danger [65,66].

Furthermore, research shows how changing the perception of an individual can change how they interact with their environment [67]. Emotional communication can be a useful tool to regulate social interactions such as mating competition, play, maternal nursing, and group defense. Harmonizing the emotional behaviors of individual animals can help other farm-animals develop more empathy and other desirable traits [68]. This may result in the entire herd developing strong social bonds and improved group coordination [69].

We are going beyond the research on emotions and their impact on individuals. We are now beginning to study how emotional contagion and emotional expressions can enhance the well-being of entire groups [70].

For instance, various species use vocal signals to show different emotional states [71]. We have also found that vocal signals strongly correlate with emotional reactivity [72]. Additionally, in a related experiment, it was found that domestic pigs exhibited behavioral and cardiac responses when they heard a distress call from another pig [73]. In a more recent study, goats showed a head-orienting response to the right side whenever they heard calls from other goats, indicating that they use parts of their left hemisphere brain actively to associate with non-threatening vocal signals [74]. These studies give us enough clues into how important vocal signals and emotional states are interconnected.

ML-based AI can help us identify the variables of emotional contagion based on vocalizations, olfactory cues, etc. to detect the outburst of a specific disease or stress (Fig. 4). This has the potential to help us improve the living conditions and well-being of farm animals significantly.

While working with emotional contagion, tools such as social network analysis can be used to assess the qualitative (e.g. agonistic) and quantitative (interaction count) data of social relations. This can help us better predict any positive and negative stimuli spreading among a group [75], and in turn, can help us avoid negative stimuli and

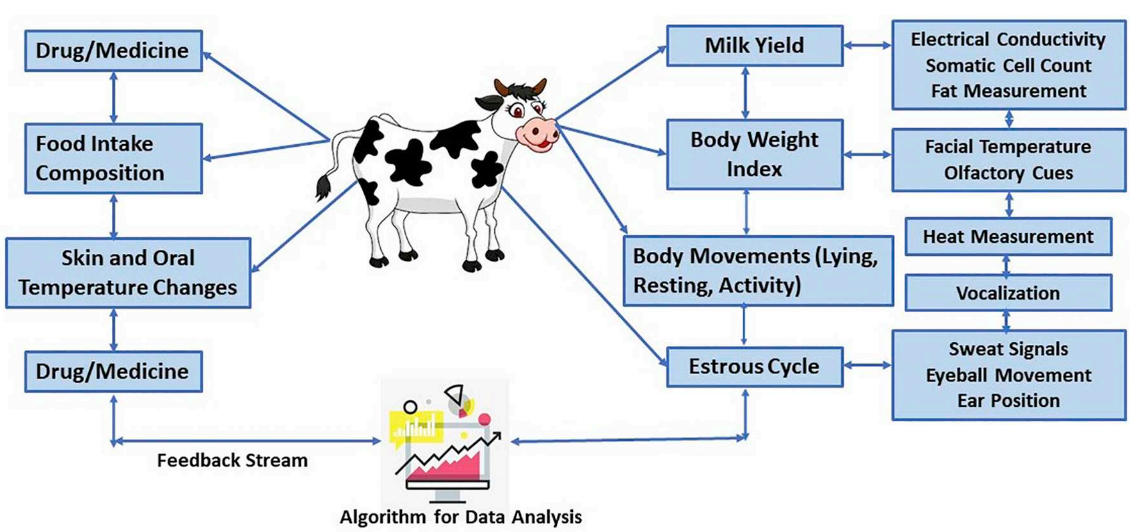

Fig. 3. A representation of how machine learning algorithms might interpret data to create optimal growth conditions in dairy farming.

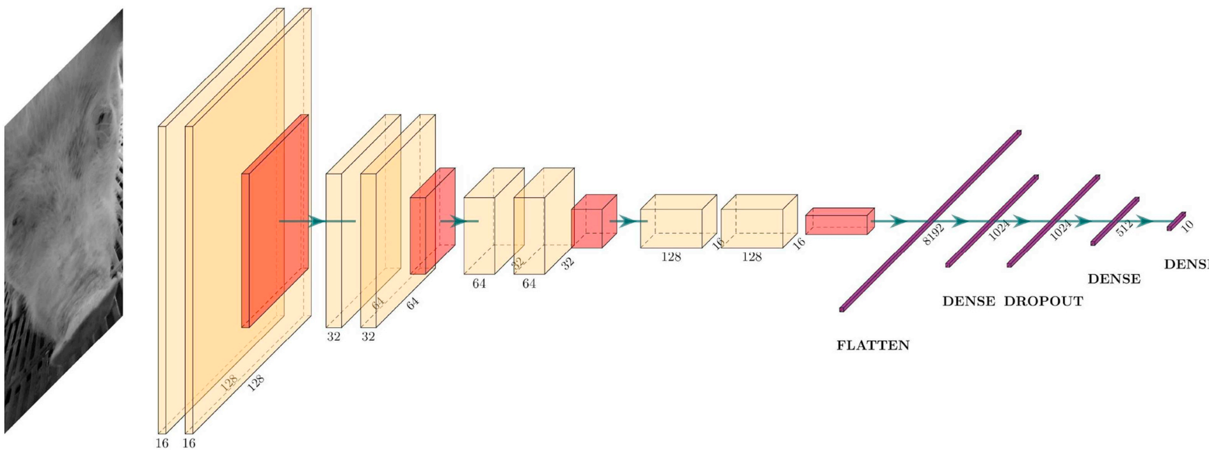

Fig. 4. Flow diagram showing the neural network for emotional contagion of farm animals. An example Convolutional Neural Network (CNN) architecture used for pig face recognition [80].

emotions over time and promote a sense of well-being among farm animals.

7. Won't technology be bad for farmers?

7.1. Farmer concerns

It is important to understand how farmers interpret the value of technology in the context of their farm. Farmers look at value to their overall farming business in adoption of the usage of big data analytics, sensor platforms and ML, and also consider whether it poses a risk to their animals and their role/identify as a good stockman by creating a physical distance between the two.

The animal farming industry is quickly becoming a hotspot for new technologies such as deep learning, AI, and ML. These smart farming technologies are being used to monitor animals [2], predict diseases [18], optimize food intake [49], and improve animal health [59]. However, these advancements also generate massive amounts of data. These data fuel ML algorithms to solve future problems. However, all is not well in the land of futuristic animal farming technologies. Three significant drawbacks are apparent.

Firstly, use of the data is itself is a problem. Vast amounts of data from the technology products and services get stored in remote cloud servers. This is often monetized for commercial benefits [2]. Big corporations such as Monsanto and John Deer now collect, use and even sell farmers data [76]. Farmers are already getting into tussles over this with big corporations. This rising tension over data misuse is a considerable threat [77]. Technology companies need to come up with better solutions to prevent misuse of their user data.

Secondly, there are a few instances where technology cannot be used effectively. In some cases, farmers are either reluctant or may not be able to use the latest technology in their farms. The access to internet and usage in the global food security strategy countries (GFSS) ranges between 10% to 50% of the population and remains a bottleneck for the adoption of the digital farming technologies [78]. Only about 25% of the mobile phone owners of the GFSS countries by the animal producers and farming households access information about agriculture and uses tools for livestock or animal production management systems through mobile apps and other means [79]. There may be several other cases where technology cannot be used effectively due to various environmental, physical, and situational constraints. The successful companies of tomorrow will have to come up with innovative workarounds around these constraints.

And finally, companies are being criticized for selling pre-mature technology to farmers, without sufficient trials or evidence. There is a strong opinion that technology companies are using farmers to validate their products and services. This allows the technology companies to de-risk themselves, but at the same time this puts farmers under more risk. Because these technologies are still in the nascent stage, any mistakes could result in costly losses for the farmers. This is especially true when it comes to predicting epidemic diseases in large scale animal farms [18].

7.2. Current challenges

Currently, available commercial sensors are vastly limited for reliable prediction and diseases management of livestock farming through continuous automated real-time monitoring. For example, there are no sensors available to measure biomarkers from the breathing space of the cows and pigs which could point out the gut microbiota or even the metabolic states of the animals. This gap calls for development of sensors and biosensing tools using ‘omics’ and non-omics approaches specific for measuring biomarkers, miRNAs and odour volatile metabolites and others. Additionally, there are specific technical challenges such as where the sensor will be positioned, what the sampling rate will be and how the data will be transmitted, among others. All these considerations have an impact on the accuracy of the algorithms as well as the scalability and the practicality of the solution that could therefore be utilized on the animal farm. Evaluating the sensor position, sampling frequency, sensor data analysis, and window size for the processing of data would help significantly to enhance the prediction of the farm animal behavior.

8. Machine learning algorithms choice for data analysis

What, and how many types of ML features are needed and which algorithms are therefore best to tackle the problem of classification and the choices can decide the desired outcome of the animal welfare evaluation. For example, from a set of 44 features, perhaps only five to seven features may be needed to yield highly accurate results. Hence, in real-time systems, large feature sets could be problematic due to computational complexity and higher storage requirements.

In addition to energy considerations, one of the key technical challenges for real-time and long-term farm animal behavior monitoring is ‘concept drifts’. Concept drift occurs when a sensor platform and data analysis system is required to adapt to a change in data distributions within the concept.

In supervised classification problems, it is generally assumed that the data in the design model is randomly selected from the same distribution as the points that will be classified in the future. This is an unrealistic assumption due to the dynamic nature of many different classification problems. For example, when a system is trained in one

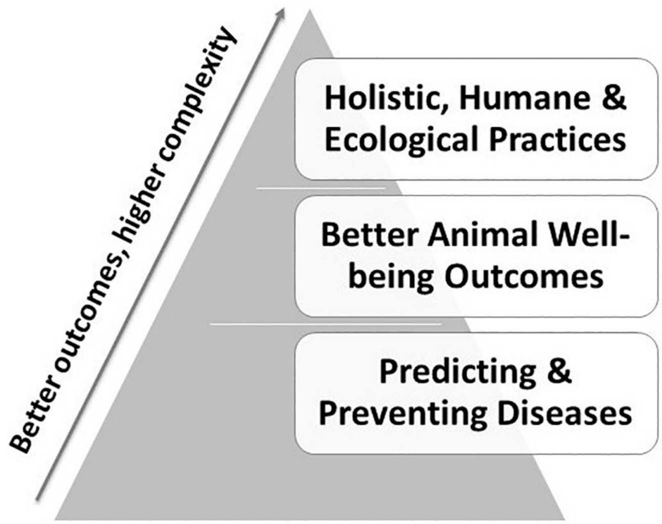

Fig. 5. The hierarchy of better animal farming outcomes. Advanced technologies have the potential to help farmers achieve better outcomes.

environment, behavioral classification of animals can also show discrepancies in performance given environment variance or heterogeneity. Such discrepancies can be due to differences in the animals (age, breed, etc.) and/or environmental characteristics (change in weather conditions, terrain elevation, type of soil, particular farm constrains, etc.).

8.1. In pursuit of more complex & better outcomes

We are already in the era of sensors, big data, and ML, and over the next decade, these advanced technologies are set to drive improved efficiencies and greater gains in animal farming. It will also lead to fewer human errors. In turn, this will improve productivity, farmer profits and animal well-being. More importantly, it has the potential to help us go beyond better profits and higher productivity by helping us achieve better animal well-being outcomes. It may also help us develop more holistic, humane, and environmentally friendly practices (Fig. 5).

9. Conclusions

The emergence of Agriculture 4.0 is fueling the growth of adoption of sensing technologies, big data, and ML in modern animal farming. In the reality of pandemic scenarios where restrictions are making it difficult for veterinarians, nutritionists, and producers to visit the farms, barns, and feed mills; real time 24/7 insights into the livestock's activity, consumption and production are needed. These insights enabled by the sensing technologies generate data which are accessed remotely resulting in lower cost and enhanced performance responding to the demands of the consumer. Although AI and ML algorithms have developed so fast, there is a lack of standardization in the collection and sharing of data globally. However as more farms get connected to technology, AI and sensing technologies will start playing a more decisive role in helping farmers see patterns and solutions to pressing problems in the modern animal farming. While there are still several unknowns, limitations, and open-ended questions, one thing is certain. In this decade, we will discover the true power of human - artificial intelligence collaborations in the livestock sector.

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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