Transforming Business through Sensors, Big Data, and Machine Learning in Modern Animal Farming

Muhammad Irfan[1], Khadija Altaf[2], Muhammad Qayyum[3], Muhammad Akhter[4], Salman Muhammad[5], Hira Somra[6], Muntazir Mehdi[7]

[1, 3, 4, 5,6]MNS University of Agriculture, Multan, Pakistan.

Fazaia Bilquis College of Education for Women, Rawalpindi, Pakistan

*Corresponding Author: Email: 2020-uam1422@mnsuam.edu.pk

Abstract: When it comes to animal production, humans have always depended on gut feelings, shared knowledge, and sensory inputs, even when domesticating animals started thousands of years ago. Thanks to this, our achievements in farming and animal husbandry have been substantial thus far. More centralized, large-scale, and efficient animal farming may be possible as a result of both the increasing demand for food and the development of sensing technologies. As we know it, it could revolutionize animal husbandry. This study takes a high-level look at the possibilities and threats that sensor technology poses to animal producers' ability to increase theirmeat output and other animal products. This study aims to investigate how sensors, big data, artificial intelligence, and machine learning may assist animal producers in improving animal comfort, increasing productivity per hectare, decreasing production costs, and increasing efficiency. It delves into the difficulties and restrictions of technology as well. This study explores the many uses of animal farming technology in order to comprehend its worth in assisting farmers in bettering the health of their animals, increasing their profitability, and decreasing their impact on the environment.

Keywords: *Cardiac disease; intelligent model; disease prediction; deep learning*

1 Introduction

Traditional animal husbandry has always been small-scale, operated by a group of people rather than an organization. Also, most farmers who raised animals did not have access to things like smartphones, affordable computers, and fast internet until around ten years ago. At the moment, both of these things are evolving at a rapid pace. The demand for meat and other animal products will increase by 70% globally over the next 30 years. We now know that as global incomes and populations have risen, so has meat consumption. Because of this, we need to boost animal output while cutting back on land, water, and other natural resource allocations. Secondly, the percentage of people accessing the internet through mobile devices has surpassed 50%. The computers on Apollo 11, the first manned spacecraft to land on the moon, were much more powerful than our current pocket-sized phones. Millions of animal producers can now access computing power because of this. Reports indicate that farmers will need to increase output by 70% in the next fifty years only to meet the global demand for meat and other animal products [1]. Given the scarcity of arable land and other natural resources, it will be imperative to develop more efficient cultivation methods in order to satisfy this surging demand.

More cattle on the land. This raises the question of whether the present approaches to animal husbandry, which depend on physical effort, are sufficient. This also means that we should find ways to enhance our animal husbandry practices for greater yields. Computers, sensors, cloud computing, machine learning, and artificial intelligence are causing significant shifts in various industries. Their efficiency and output are enhanced [2]. Learning how these innovative tools could boost crop productivity is an important area to look into.

Key cost drivers in animal farming

Animal husbandry costs are primarily affected by the stocking rate, which is the maximum number of animals allowed to graze on a given area of land for a given time period. Feed and disease control are the two main costs in animal production, which farmers themselves admit. Farmers can increase efficiency and decrease production costs by increasing the number of animals raised in a given system, taking advantage of economies of scale [3]. However, physical interventions are necessary in some way or another for most modern animal farming methods. People oversee the production process, assess the rates of food provision, and identify and treat illnesses. The result is a decrease in the total number of animals that can receive care. A lower number of people caring for a far higher number of animals would, in principle, remove the most significant barrier to increasing output and optimizing profits.

• Mechanistic models, sensors, big data & advanced algorithms

We use mechanical models in complex systems to understand why things happen the way they do. A mechanistic model is expected to provide a thorough explanation for the patterns seen in the system under study. When dealing with complex circumstances involving several factors, this technique shines. In many cases, this means that the problem cannot be solved by doing experiments alone. However, solving such a complex problem calls for the systematic collection and analysis of massive volumes of data. Animal farming mechanistic models can solve complex problems like finding the optimal nutrient composition of feed, assessing animal management for performance, finding ways to reduce nutrient excretion into the environment, and forecasting results in new situations.

The use of mechanistic models in animal husbandry requires a large and diverse dataset. Information on local weather, air quality, animal vocalizations, visual records of various animal motions, and similar data on animal behavior are all examples of what could fall into this category. Acquiring data in real time is made efficient by using multiple sensors. But obviously, such a system needs to be able to store a lot of audio, video, and textual data. No ordinary computer could possibly store and process such massive amounts of data every single day of the year. Its computing and storage capacities will be exhausted very soon. Anything that can detect or keep tabs on physical, chemical, biological, or any other kind of event is called a sensor.

A tool that humans or machines can use to record and gather data pertaining to mechanical properties or a mix of these attributes. The needs of the animal husbandry industry dictate the classification of sensor technology. Sensors for precise milking robots and feeding systems are part of this category, as are applications designed for specific species, such as those found in pigs, ruminants, and poultry. Cameras, infrared thermal imaging sensors, thermometers, radio frequency identification tags, accelerometers, motion detectors, pedometers, microphones, and face recognition machines are all examples of hardware sensors.

Among the many practical applications of these sensors are temperature regulation, weight estimation, animal behavior, emotional contagion, feed dosage, water consumption, and many more. Another way to classify sensors is by whether they are invasive or not and whether they are wearable or not. Big data offers a scalable way to store massive amounts of data on a distant computer, which is essential for integrating advanced technology in animal husbandry. Algorithms powered by advanced AI and ML can sift through this mountain of data, make predictions, and notify farmers of any outliers (Fig. 1). The combination of sensors, big data, and robust AI and ML algorithms in the field of animal agriculture thus provides a whole solution. In this paper, we collectively refer to these various technological advancements as “advanced technologies” on multiple occasions.

1. Advanced technology and animal farming

• *Finding ways to optimize performance*

In practice, these advanced technologies can be used to find the best answers to different problems in animal husbandry. Case in point: finding the most cost-effective ways to increase

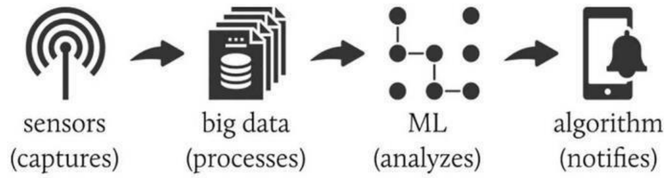

Fig. 1. The collection of technologies that we refer to as advanced technologies can help animal farmers create better outcomes.

Improving output, maximizing effectiveness, and creating ideal dietary formulas [4]. Relevant and contextually appropriate solutions can be generated by advanced models that combine aspects like heredity, environment, and managerial priorities. When a system gathers and analyzes more diverse datasets, it increases the probability of achieving optimal and proper responses [6]. Another perk of this method is that it would give farmers a data-driven or evidence-based strategy.

- ## Understanding complex systems

Thanks to technological progress, we can now study complex systems, like biological ones, from the inside out. Data analysis can help us understand complex animal systems better by allowing us to extract important information [6]. Finding the fractional rates of rumen degradation [7] or exact rates of mammary cell development [8] are only two examples of how they might help us organize experimental data and calculate essential parameters. Still, anything can go wrong with technology, no matter how sophisticated. They are great tools for finding areas where knowledge is missing or assumptions about system management are wrong [6]. The inability to faithfully reproduce reality serves a useful purpose in that it highlights unanswered questions, potentially erroneous assumptions, or a lack of data. Though it may not always provide desirable outcomes, incorporating cutting-edge technology into animal husbandry can help us learn more and better understand animal systems.

- ## Recognizing complex patterns

Data in many formats, such as text, audio, video, and images, can be expertly analyzed by modern technology. After that, advanced algorithms can make sense of the datasets by classifying them or predicting future trends. Animal production systems have used sophisticated data analysis and algorithms for pattern recognition-based disease detection and animal monitoring [6]. To monitor changes in animal behavior, for example, scientists have developed a plethora of sensors, in addition to sophisticated data processing and machine learning models. These alterations may point to changes in temperature, damage, metabolic state, or general health. Animal identification is another application for these sensors [6]. At the moment, we have a variety of sensors that can correctly classify animal behaviors, including sleeping, thinking, eating, and moving around. Combining optical sensors [10], 3-axis accelerometers and magnetometers [9], or depth video cameras [11] with machine learning models effectively classifies and predicts animal behavior, according to research articles.

In addition, we present more examples of how applying machine learning and big data could help diagnose animal diseases earlier than before. The noises generated by grill chickens, both healthy and infected with Clostridium perfringens, were recorded by Sadeghi et al. [12] as an example. Five datasets were identified and analyzed by the researchers using an ANN model. This model successfully differentiated between sick and healthy birds at 66.6% accuracy on day 2 and 100% on day 8 after infection. Identifying or even anticipating disease outbreaks early is possible because infections can produce observable differences in movement patterns [13] and surface temperature of animals [14].

• Predictive abilities

The ability of contemporary technology to foretell and project outcomes of economic importance, like BW, milk yield, or egg production, is now at our fingertips. An example of this is using a support vector machine classification model to precisely predict the. When the variations in the herd's body weight over time are known, the body weight (BW) of individual cattle can be calculated. When there were insufficient data points for body weight measurements, and longer-term predictions were required, this Method performed better than using individual animals' regression models. In order to track the BW of developing pigs, several researchers have proposed using visual image analysis platforms based on machine vision. These researchers include Pomar and Remus (5), Parsons et al. (16), and White et al. (17). Appropriate feed allocations can be assessed using this method. Such predictive abilities could revolutionize animal production by bringing about new efficiency and larger advantages.

1. Identifying, predicting & preventing diseases using sensors

As said before, finding, forecasting, and preventing animal diseases all add up to a hefty sum. There are three significant ways that farmers typically handle animal infections: either doing nothing, actively seeking out veterinary help, or using a mix of antibiotics and veterinarian intervention.

Modern technological advancements, such as sensors, big data, AI, and ML, present a fresh chance for farmers. With this technology, vital signs, including animal movement, air quality, and food and fluid intake, can be continuously monitored, rather than problems being addressed after the fact or proactive measures like visiting veterinarians. Farmers can now anticipate, detect, and proactively reduce disease outbreaks, even before they develop on a large scale, thanks to continuous data collection and advanced artificial intelligence and machine learning algorithms [69-73]. To clarify, sensors can actually track the vital signs of animals, not just people, all the time. There are two significant benefits to this method. It is possible to reduce production costs by using one of these methods to reduce the number of farmers required to care for a greater number of animals. Also, before any visible signs appear, this technique might notify farmers that a disease may be on the horizon. As a result, farmers will be able to take swift action to prevent catastrophic damages [18].

Extensive livestock facilities hold a myriad of animals collectively and can be severely damaged during an epidemic of a highly contagious disease. Without immediate preventative actions, the farmer will have a hard time controlling the spread of the infectious disease in this setting. When symptoms first appear, it is often too late to do anything about it. A combination of animal deaths, worse health outcomes, and financial setbacks can result from an uncontrolled disease's rapid expansion [19]. On the other hand, a state-of-the-art farm with a network of sensors can immediately notify the farmer of any abnormal behavior, even in its early phases.

• Sensors, big data & machine learning

The ability to quickly collect, process, and analyze large datasets is a hallmark of automated systems.
They cannot make educated choices in the absence of evidence. They can help people make better decisions by gathering and analyzing large amounts of data. On a farm, a number of sensors can let farmers keep tabs on how animals are behaving right now [20]. In order to track, quantify, and understand changes in animal behavior, sophisticated algorithms can use massive datasets. It can help farmers make better decisions and act faster when diseases strike [21, 22].

At this time, there are a variety of sensors available to farmers that can track changes in animals' mobility, food intake, sleeping habits, and even the air quality in their shelters. A computer capable of handling massive volumes of data stores and processes the initial data. In the end, ML algorithms highlight any differences or breaks from the norm. Early detection of several diseases in pigs and lambs has been made possible through the use of sensors, big data, and ML algorithms. This is accomplished by observing sluggish movement, delayed reaction times, and reduced activity levels that occur prior to the emergence of other outward signs of illness [18, 19, and 23]. However, farmers find it difficult to notice these changes using unaided human eyesight when dealing with large groups of animals. Similarly, it is difficult for a farmer or caregiver to notice changes in Watching a sick animal's unusual eating habits, drinking habits, and bodily movements within a large animal population. Quickly predicting and avoiding disease outbreaks can be made possible by sensors, big data, and machine learning, which can be vital for farmers [24].

For instance, air sensors used in the poultry industry can now predict when coccidiosis, a gastrointestinal disease that can spread quickly among birds without apparent symptoms, will start [25]. One way to detect this sickness is to continuously evaluate the air quality. There is a clear association between the number of sick birds and the increase in airborne volatile organic compound (VOC) concentrations. Even before a farmer or doctor may notice the change, air monitors can detect it. Farmers can quickly take action to stop the spread of the disease if they are informed. Multiple animals' lives are spared, and financial losses are reduced by using this method. Similarly, forecasting many diseases in larger animals is now possible with the use of sensors, big data, and robust algorithms, which is much better than what humans are capable of. To illustrate the point, cows with mastitis, an udder disease, produce less milk overall and of lower quality. It has long been accepted that somatic cell count (SSC) and electric conductivity (EC) measures are the gold standards for diagnosing mastitis [26]. Having said that, these manual readings often end up being inaccurate, unstable, and useless. Automatic sensors and algorithms can now reliably collect data, predict when cows are likely to get mastitis, and take measures to reduce that risk [27].

Early disease detection tools have been around for a while. Modern technology allows us to do this with tools like RtPCR. However, they were too costly to be applied on a massive basis. Sensors, extensive data, and ML algorithms now provide a significant cost advantage over conventional detection methods (Fig. 2). For a fraction of the cost, they can predict when deadly viruses like African swine flu will spread and stop them in their tracks [19]. Significantly, state-of-the-art tech can predict the spread of many infectious diseases well in advance of their general epidemic (Table 1). On the flip side, computers can analyze animal movements and predict when a condition, like lameness, will manifest. During the preclinical stage of lameness, changes in mobility, overuse of particular body parts, and inactivity in other areas are reliable indicators [28]. The third most crucial agricultural disease is lameness, drastically reducing milk production and increasing the risk of injury [29]. Farmers can lessen the impact of significant financial losses by planning ahead for lameness. The mobility of infected pigs is reduced, according to studies. It can drop by as much as 10% in the first two days of infection. The separation of sick animals from healthy ones can be facilitated in this way, preventing the spread of disease [19]. In the end, environmental sensors, such as Farmers, can help reduce the occurrence of bacterial infections and diarrhea in pigs by adjusting humidity, gas generation, and temperature [25]. All of these cases show how sensors, big data, and AI could help farmers avoid costly and invasivedisease predictions and prevention.

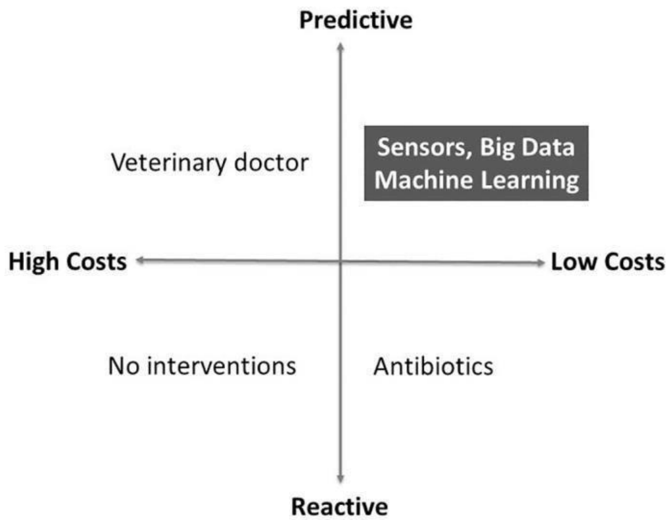

Fig. 2. Difference between predictive and reactive paradigms of managing diseases among animals.

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]

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

2. Improving animal health using facial recognition systems

It is an important task to be able to identify a particular animal in a group. For a long time, herd management has been a huge challenge, especially for large-scale producers. To achieve this on a large scale, no practical and compassionate technological alternatives existed before. Radiofrequency identification tags offered the fastest answer. Their efficiency was limited, but they were cheap and did the job. RFID tags aren't without their flaws.

Farmers used to have to put the tags in each animal's ear. In addition to being a painstaking ordeal for the farmer, this also distressed the animals. In addition, problems emerged when trying to scan many RFID tags at once. Because of this, farmers couldn't get useful information when animals migrated in groups, which happens quite often. Last but not least, the expensive RFID scanners installed on farms were vulnerable to bodily harm. Human face recognition has been the subject of much research in the last several decades. Several security-related applications have used facial recognition software, including improved surveillance systems, threat detection, and access control. New face recognition algorithms can now identify and classify a wide range of animal behaviors. Here is the user's text: "[31]." Previous research on sheep [35], pigs [31], and cattle [32–34] found promising results when studying facial expressions. Previous Eigen faces-based face recognition algorithms did, however, have certain limitations. To give only one example, it can detect patterns with an accuracy of only 77% [36]. A large-scale farmer handling several animals would not find the discrepancy practicable due to its huge size.

Hardware and software advancements in recent decades have allowed us to quickly handle large amounts of raw data and produce valuable results. The VGG-face model [37], Fisherfaces [38], and convolutional neural networks are three separate face recognition approaches that can now be used rather than just one. This non-invasive imaging technology has a 96.7% success rate in identifying specific pig faces in a farm setting. With this gadget, farmers may finally say goodbye to useless RFID tags and hello to efficient, widespread animal monitoring. This can help farmers save a ton of money and cut down on labor requirements.

These technologies are now entering a phase of development where they will be used in real agricultural fields rather than just in labs. For example, a 98.3 percent success rate in identifying individual cow faces has been achieved by merging the cow-face detection system with the PANSNet-5 identification model [40]. These numerous face detection and recognition algorithms can currently differentiate between different animal faces in complicated real-time scenarios, regardless of the amount of available data or the degree of shape distortion [41]. In addition to improving our knowledge of the animal's traits, these advances in face recognition have a number of other potential practical applications outside animal identification. Mental and emotional condition. These days, we can tell an animal's emotional state only by watching its eye and ear movements. When an animal's eyelids are partially closed, and its ears are pointed backward, it shows that it is relaxed. On the flip side, animals who are agitated or distressed could have their ears perked up and more sclera showing [42].

Now, with the help of technology, we can learn about the difficulties animals face even when we're not physically there. For example, it's possible that there's a problem with the feeding stations if we see a lot of distressed cows in the feedlots. More research is required to confirm this finding. These studies can occasionally reveal facts that the general public fails to notice, like the dearth of feeding spots [42].

It may also help us recognize signs of suffering in sheep. It is feasible to find signs of disease, physical damage, or predator attacks while conducting a more comprehensive examination. The Sheep Suffering Facial Expression Scale (SPFES) allows for precise evaluation of discomfort and suffering in sheep [43]. Technological progress is making it easier and more accessible for farmers to monitor their cattle in real-time and detect problems with greater precision. The health and welfare of the animals may improve as a result [44].

3. Gains in optimizing feed efficiency & energy intake

Between forty percent and sixty percent of a dairy farm's total expenditures can be attributable to feed [45]. One of the biggest drains on this sector's coffers is raising animals for food [46]. Animal production is adversely affected when they do not receive enough water and food. Modern farmers keep a close eye on this. They can now accomplish this with more accuracy thanks to technological advancements.

The amount of food and liquid consumed may vary significantly. There are a number of factors that can significantly affect feed intake, including calving, heat, and feed mix. Proper nutrition for animals requires a feed that strikes a balance between bulky (low energy, high volume) and concentrated (high energy, low volume) components [50]. Animalmetabolism can be improved by utilizing optimal feed ratios.

The feed efficiency can be calculated by considering the following factors: feed intake, animal weight gain [46], and, if applicable, milk and egg output. Unfortunately, manual sorting isn't always an option because these traits depend on so many diverse and non-linear factors. With the use of RGB-D cameras, farmers can more precisely measure how much feed each cow consumes [51]. In addition, TDIDT, ENET, SSD, ARIMA, and CNNs are just a few of the advanced algorithms that farmers can use to fine-tune and improve feed expenditures according to their animals' individual needs [46, 49-52]. As shown in Table 2.

Accurate predictions of farm animal productivity can be obtained using technological means [53]. Parameters, including body condition score (BCS), milk yield components, and parity, can be used to assess their energy expenditures when nursing. Hence, using the existing on-farm data, we can approximate the metabolic state of cows. Farmers can benefit from ML techniques by precisely assessing different parts of their dairy businesses. Some examples of these are determining breeding values [53], predicting milk yield [54], calving time [55], and diagnosing mastitis [57, 58] (Fig. 3). Sensors also have several other uses, such as helping to track changes in cow behavior to determine whether they are in estrus [21] or if they are actively digesting their food efficiently [49]. This strategy will help farmers succeed in the long run by increasing their output of high-quality milk [51, 59].

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 NET) 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 concentrated milk.	
Production by each cow	[50]	
Convolutional Neural Networks (CNNs)	RGB camera, RFID for cow feed intake, and Milk production measurement and frequency	[51]

Make it possible for them to earn more money. Using motion and sound sensors to track animal behavior, acidosis in cows can be detected [60]. Furthermore, there is a 90% success rate in adequately predicting when calves will be born. This may supersede more expensive, time-consuming, and often inaccurate solutions. The pain and difficulties of giving birth can be lessened if the exact time of delivery can be predicted. When it comes to managing groups of animals, this is a huge step forward [61].

4. Towards better outcomes

- Lower antibiotic usage & fodder requirements

This study found that farmers and animal health can benefit from using sensors, bigdata, and machine learning. It can also help us move towards a future of less cruel and eco-conscious farming, which is a little-known fact. It could significantly contribute to cutting down on feed and antibiotic usage. As a result, lower antibiotic resistance [63] and more carbon sequestration [62] may occur. In addition, technological advancements can help us better understand the feelings of animals.

- Artificial intelligence for emotional contagion

According to social psychologists, "emotional contagion" is when people start acting out other people's feelings. On the other hand, it might be a sign that someone is easily affected by the feelings of those around them while they are living in close quarters with them [64]. The primary function of emotions in animals is to enable a quick reaction for efficient environmental coping. As a group, they can move closer to the goal or away from danger more easily [65, 66].

Additionally, research shows that changing people's perceptions of an

The way a person engages with their immediate environment is malleable [67]. A variety of social interactions, such as mating contests, play, nursing, and group defense, can be effectively managed through emotional communication. One way to help other farm animals develop empathy and other desirable traits is to have them synchronize their emotional actions with one another [68]. This may result from a stronger sense of group cohesion and more robust social bonds among the herd as a whole [69].

The impact of emotions on people is an area where we are expanding our studies. Emotional contagion and emotional expressions are currently our primary research foci because of their potential to boost the health of huge populations [70]. For instance, some animals use vocal signals to convey different types of emotions [71]. A strong Correlation between vocal cues and emotional responsiveness has also been shown by us [72]. Separate research found that when domestic pigs heard a distress call from another pig, they exhibited behavioral and cardiac responses [73]. A recent study found that when goats heard other goats, they tended to tilt their heads to the right. According to this, goats utilize their left hemispheres to process and correlate non-threatening voice signals [74]. These studies shed enough light on the relationship between voice cues and emotional states to warrant further inquiry.

Machine learning-based AI can analyze vocalizations, olfactory signals, and other pertinent data to help determine the components contributing to emotional contagion. As shown in Figure 4, this analysis can be utilized to identify the beginning of a particular illness or stress. This can significantly improve the living conditions and general well-being of farm animals. Emotional contagion research can benefit from social network analysis by assessing quantitative (number of interactions) and qualitative (kind of relationship, such as agonistic) data. Improved emotional regulation and cattle welfare can result from this, as might increase our capacity to foresee the spread of positive and negative stimuli within a group [75].

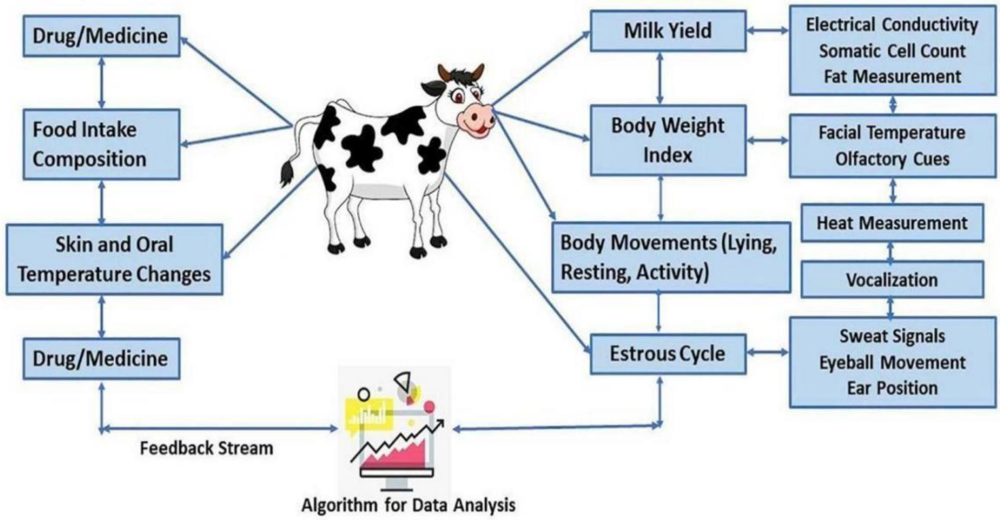

Fig. 3. A representation of how machine learning algorithms might interpret data to create optimal growth conditions in dairy farming.

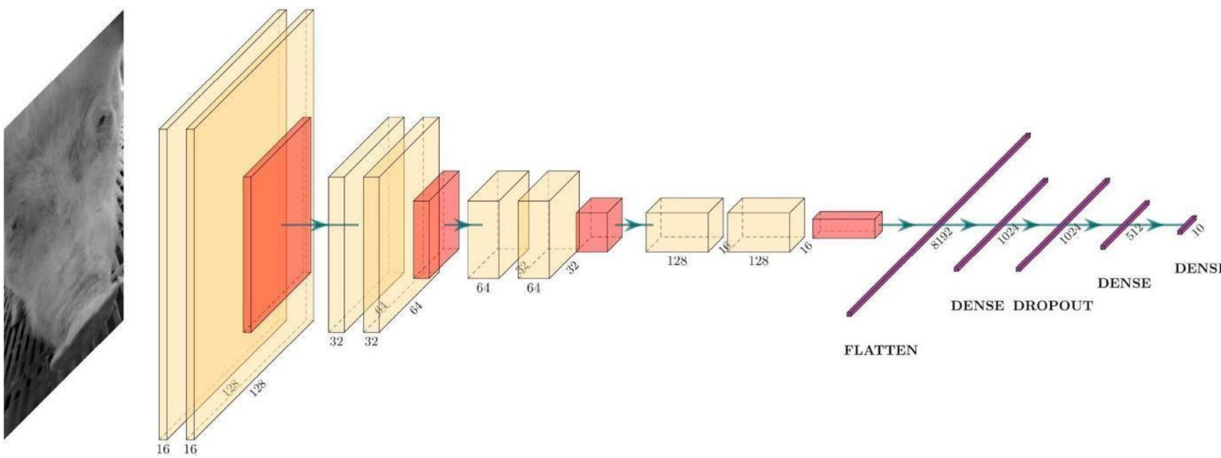

Fig. 4. Flow diagram showing the neural network for emotional contagion of farm animals. An example of Convolutional Neural Network (CNN) architecture used for pig face recognition [80].

5. Won't technology be bad for farmers?

- Farmer concerns

It is critical to understand how farmers value technology in relation to their farming operations. As they weigh the pros and cons of physical barriers, farmers consider the advantages of big data analytics, sensor platforms, and machine learning for their farming operations, as well as the risks to their animals and their credibility as competent livestock managers.

New, state-of-the-art technologies like deep learning, AI, and ML are quickly finding a home in the animal husbandry industry. Optimal food consumption [49], illness forecasting [18], animal monitoring [2], and overall animal well-being [59] are all achieved using smart agricultural technologies. But along with these technical advancements come massive amounts of data. To tackle future problems, machine learning algorithms will use this data as input. But, even with all the advancements in modern animal husbandry, there are still problems. It is easy to see three significant drawbacks.

The data's own use presents an issue first and foremost. Distant cloud computers store massive amounts of data produced by technological goods and services. This is often used to gain an advantage for businesses [2]. Nowadays, prominent companies such as John Deere and Monsanto collect, use, and even trade farmers' agricultural data [76]. On this issue, farmers are currently involved in disputes with major firms. An increasing number of people are worried that data exploitation could have serious consequences [77]. To prevent the misuse of its consumers' data, tech companies need to come up with better solutions.

Additionally, there are specific cases where technology does not work. Occasionally, farmers hesitate or run across obstacles when trying to implement cutting-edge technology on their farms. In countries that are part of the global food security strategy (GFSS), anywhere from 10% to 50% of the population has access to and uses the internet. The widespread adoption of digital farming technology is hindered by its restricted availability [78]. A quarter of mobile phone owners in GFSS countries use their phones to get agricultural data and use tools for managing cattle or animal production systems [79]. This demographic consists largely of farmers and those who work on the family farm. Various environmental, physical, and situational constraints might prevent technology from being used efficiently in many situations. Businesses will have to get inventive to find ways around these restrictions if they want to be successful in the future.

A lack of sufficient studies or supporting evidence has also led to criticism of corporations for promoting emerging technologies to farmers. Many people think that digital corporations are taking advantage of farmers to prove their claims for their gifts and supplies. This puts farmers in danger while allowing digital companies to reduce their risk. Due to these technologies' immaturity, farmers risk suffering enormous financial losses should something go wrong. For large-scale livestock farms, this is especially true when trying to predict the spread of epidemic diseases [18].

- ### Current challenges

The current selection of commercially available sensors for use in automated, continuous, real-time monitoring of livestock is very limited, making it difficult to make reliable predictions and implement efficient management practices in this area. Unfortunately, a dearth of sensors can detect biomarkers in pig and cow exhaled air that could shed light on the animals' metabolic states and gut flora. To address this disparity, new biosensing devices and sensors combining 'omics' and non-omics approaches are required for the detection of biomarkers, miRNAs, volatile metabolites linked to smells, and other compounds. In addition, there are clear technological hurdles to think about, such as finding the best spot for the sensors, deciding on the right sampling rate, and coming up with a good way to transmit the data. These issues impact the algorithms' accuracy, the solution's scalability, and the animal farm's practicality. To significantly enhance the precision of forecasting the behavior of farm animals, it is necessary to evaluate the sensor locations, sampling rates, data analysis methods, and processing window sizes.

6. Machine learning algorithms choice for data analysis

To get the desired result in animal welfare evaluation, what kinds of machine learning characteristics are necessary, and which algorithms work best for classifying data? For example, it's conceivable that merely a subset of five or seven traits, out of a total of forty-four, is adequate to get extremely accurate results. Consequently, large feature sets could be problematic in real-time systems because of the extra storage and processing requirements.

The incidence of 'idea drifts,' in addition to energy limits, is a major technical hurdle to real-time and long-term monitoring of farm animal behavior. When a concept's data distributions change, the sensor platform and analysis system will need to adapt, which can lead to drifting. It is often assumed that in supervised classification problems, the data used to train the model comes from the same distribution as the points to be classified later. The dynamic nature of many categorization problems renders this assumption unworkable. One example is when a system is trained to do a specific task. Behavioral taxonomies can also show how environmental diversity and variation affect animal performance. Animal characteristics (such as breed and age) and environmental variables (including shifts in weather, geography, soil, and farm-specific constraints) can both contribute to these discrepancies.

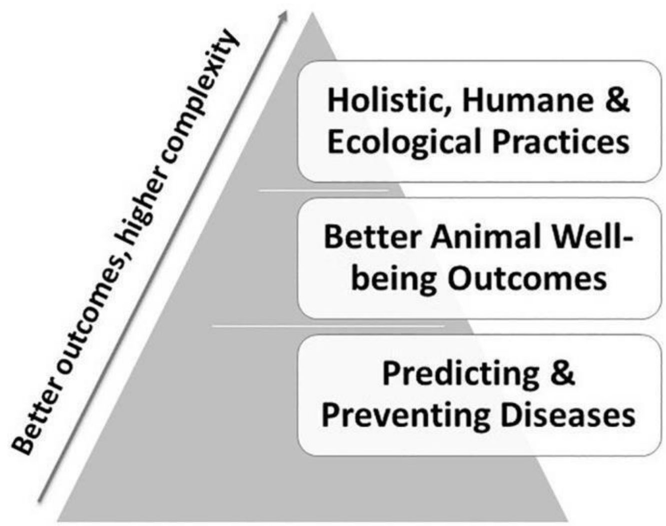

Fig. 5. The hierarchy of better animal farming outcomes. Advanced technology has the potential to help farmers achieve better outcomes.

- **In pursuit of more complex & better outcomes**

Machine learning (ML), big data, and sensors are the hallmarks of the modern era. These advanced technologies are anticipated to improve animal husbandry's efficiency and produce greater benefits in the next decade. There will be fewer mistakes made by humans as a result as well. Agricultural profits, animal welfare, and overall efficiency will all see significant improvements as a result. In addition, it can help us achieve more than just financial benefits and efficiency advantages by enabling better animal welfare results. Figure 5 shows that it may also help us create holistic, caring, and environmentally responsible approaches.

2. Conclusions

The rise of modern animal husbandry is being propelled using sensing technologies, big data, and machine learning, all of which are part of Agriculture 4.0. There is an urgent need for real-time access to data on livestock behavior, feed consumption, and output amid a pandemic when producers, nutritionists, and vets cannot physically visit farms, barns, and feed mills. Accessible remotely, useful data can be gathered using sensing devices. Meeting customer needs is effectively achieved through cost reduction and better performance. Standardization in worldwide data collection and sharing is noticeably lacking despite the fast growth of AI and ML algorithms. Using artificial intelligence and sensing technologies to help farmers spot trends and find solutions to pressing problems in modern animal husbandry will be more critical as farms get more linked to technology. Even though there are many restrictions, unknowns, and unanswered questions, one thing is sure. In the next 10 years, we will learn how the livestock business may benefit from partnering with artificial intelligence.

Declaration of Competing Interest

The writers now state that they are free from all personal or financial relationships orconflicts of interest that may have affected the results reported in this work.

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 solu- tions, 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.
7. 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.
8. J. Dijkstra, J. France, M.S. Dhanoa, J.A. Maas, M.D. Hanigan, A.J. Rook, 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.
9. 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.

10. 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.
11. 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.
12. 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.
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 ther- mography, Proc. Int. Conf. Informat. Contr. Autom. Robot. (2019) 29–31.
14. J. Alonso, A. Villa, A. Bahamonde, Improved estimation of bovine weight trajec- tories 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 effec- tiveness 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. VanderWaal, 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, Á.M. Ramos, J.M. Sánchez-Vizcaíno, Motion-based video monitoring for early de- tection of livestock diseases: the case of African swine fever, PLoS One 12 (9) (2017), https://doi.org/10.1371/journal.pone.0183793.
19. A. Nasirahmadi, B. Sturm, A.C. Olsson, K.H. Jeppsson, S. Müller, S. Edwards, 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) 475–481, https://doi.org/10.1016/j.compag.2018.12.009.
20. L. Riaboff, S. Poggi, A. Madouasse, S. Couvreur, S. Aubin, N. Bédère, E. Goumand, A. 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.
21. 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.

22. T. Van Hertem, E. Maltz, A. Antler, C.E.B. Romanini, S. Viazzi, C. Bahr, A. 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) 4286–298, https://doi.org/10.3168/jds.2012-6188.
23. 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) 505–513, https://doi.org/10.1016/j.compag.2019.04.029.
24. 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.
25. 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.
26. 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.
27. 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.
28. 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.
29. 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.
30. 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.
31. 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.
32. 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.
33. 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.

34. 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.
35. N. Wada, M. Shinya, M. Shiraishi, Pig face recognition using Eigenspace method, ITE Trans. Media Techn. Appl. 1 (4) (2013) 328–332.
36. O.M. Parkhi, A. Vedaldi, A. Zisserman, Deep Face Recognition, (2015). 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.
37. 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.
38. 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.
39. 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.
40. 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.
41. 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.
42. 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.
43. D. Amaral-Phillips, What Does it Cost to Feed your Cows? https://afs.ca.uky.edu/ files/what_does_it_cost_you_to_feed_your_cows.pdf, (2020).
44. 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.
45. M.H. Ghaffari, A. Jahanbekam, H. Sadri, K. Schuh, G. Dusel, C. Prehn, J. Adamski, B. 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.
46. 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.2019.105124.
47. 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.2019-16575.
48. R. da Rosa Righi, G. Goldschmidt, R. Kunst, C. Deon, C.A. da Costa, Towards combining data prediction and internet of things to manage milk production on dairy cows, Comput. Electron. Agric. 169 (2020) 105156, , https://doi.org/10. 1016/j.compag.2019.105156.

49. R. Bezen, Y. Edan, I. Halachmi, Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms, Comput. Electron. Agric. 172 (2020) 105345, , https://doi.org/10.1016/j.compag.2020.105345.
50. X. Huang, Z. Hu, X. Wang, X. Yang, J. Zhang, D. Shi, An improved single shot Multibox detector method applied in body condition score for dairy cows, Animals 9 (7) (2019) 470, https://doi.org/10.3390/ani9070470.
51. S. Shahinfar, H. Mehrabani-Yeganeh, C. Lucas, A. Kalhor, M. Kazemian, K.A. Weigel, Prediction of breeding values for dairy cattle using artificial neural networks and neuro- fuzzy systems, Comput. Math. Meth. Med. (2012), https://doi. Org/10.1155/2012/127130.
52. D. Gianola, H. Okut, K.A. Weigel, G.J.M. Rosa, Predicting complex quantitative traits with Bayesian neural networks: a case study with Jersey cows and wheat, BMC Genet. 12 (1) (2011) 87, https://doi.org/10.1186/1471-2156-12-87.
53. S. Shahinfar, D. Page, J. Guenther, V. Cabrera, P. Fricke, K. Weigel, Prediction of insemination outcomes in Holstein dairy cattle using alternative machine learning algorithms, J. Dairy Sci. 97 (2) (2014) 731–742, https://doi.org/10.3168/jds.2013-6693.
54. M. Borchers, Y.M. Chang, K.L. Proudfoot, B.A. Wadsworth, A.E. Stone, J.M. Bewley, Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle, J. Dairy Sci. 100 (7) (2017) 5664–5674, https://doi.org/ 10.3168/jds.2016-11526.
55. D. Cavero, K.H. Tölle, C. Henze, C. Buxadé, J. Krieter, Mastitis detection in dairy cows by application of neural networks, Livest. Sci. 114 (2–3) (2008) 280–286, https://doi.org/10.1016/j.livsci.2007.05.012.
56. Z. Sun, S. Samarasinghe, J. Jago, Detection of mastitis and its stage of progression by automatic milking systems using artificial neural networks, J. Dairy Res. 77 (2) (2010) 168–175, https://doi.org/10.1017/S0022029909990550.
57. Q. Fu, W. Shen, X. Wei, Y. Zhang, H. Xin, Z. Su, C. Zhao, Prediction of the diet energy digestion using kernel extreme learning machine: a case study with Holstein dry cows, Comput. Electron. Agric. 169 (2020) 105231, https://doi.org/10.1016/ j.compag.2020.105231.
58. N. Wagner, V. Antoine, M.M. Mialon, R. Lardy, M. Silberberg, J. Koko, I. Veissier, Machine learning to detect behavioural anomalies in dairy cows under subacute ruminal acidosis, Comput. Electron. Agric. 170 (2020) 105233, https://doi.org/ 10.1016/j.compag.2020.105233.
59. A.S. Keceli, C. Catal, A. Kaya, B. Tekinerdogan, Development of a recurrent neural networks- based calving prediction model using activity and behavioral data, Comput. Electron. Agric. 170 (2020) 105285, https://doi.org/10.1016/j.compag.2020.105285.
60. Can Cows Help Mitigate Climate Change? Yes, they can! https://daily.jstor.org/ can-cows-help-mitigate-climate-change-yes-they-can/, (2020).
61. WHO, Antimicrobial Resistance in the Food Chain, https://www.who.int/foodsafety/areas_work/antimicrobial-resistance/amrfoodchain/en, (2020).
62. J. Tsai, E. Bowring, S. Marsella, W. Wood, M. Tambe, A study of emotional con- tagion with virtual characters, Int. Conf. Intell. Virt. Agent (2012) 81–88.

63. M. Mendl, O.H. Burman, E.S. Paul, An integrative and functional framework for the study of animal emotion and mood, Proc. Biol. Sci. 277 (1696) (2010) 2895–2904, https://doi.org/10.1098/rspb.2010.0303.

64. E.S. Paul, E.J. Harding, M. Mendl, Measuring emotional processes in animals: the utility of a cognitive approach, Neurosci. Biobehav. Rev. 29 (3) (2005) 469–491, https://doi.org/10.1016/j.neubiorev.2005.01.002.

65. E.J. Harding, E.S. Paul, M. Mendl, Cognitive bias and affective state, Nature. 427 (6972) (2004) 312, https://doi.org/10.1038/427312a.

66. B.L. Fredrickson, C. Branigan, Positive emotions broaden the scope of attention and thought- action repertoires, Cognit. Emot. 19 (3) (2005) 313–332, https://doi.org/ 10.1080/02699930441000238.

67. M. Špinka, Social dimension of emotions and its implication for animal welfare, Appl. Anim. Behav. Sci. 138 (3–4) (2012) 170–181, https://doi.org/10.1016/j. applanim.2012.02.005.

68. J.L. Edgar, C.J. Nicol, C.C.A. Clark, E.S. Paul, Measuring empathic responses in animals, Appl. Anim. Behav. Sci. 138 (3–4) (2012) 182–193, https://doi.org/10. 1016/j.applanim.2012.02.006.

69. Ahmed, F., Asif, M. and Saleem, M., 2023. Identification and Prediction of Brain Tumor Using VGG-16 Empowered with Explainable Artificial Intelligence. International Journal of Computational and Innovative Sciences, 2(2), pp.24-33.

70. Saleem, M., Khan, M.S., Issa, G.F., Khadim, A., Asif, M., Akram, A.S. and Nair, H.K., 2023, March. Smart Spaces: Occupancy Detection using Adaptive Back-Propagation Neural Network. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-6). IEEE.

71. Athar, A., Asif, R.N., Saleem, M., Munir, S., Al Nasar, M.R. and Momani, A.M., 2023, March. Improving Pneumonia Detection in chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-7). IEEE.

72. Abualkishik, A., Saleem, M., Farooq, U., Asif, M., Hassan, M. and Malik, J.A., 2023, March. Genetic Algorithm Based Adaptive FSO Communication Link. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-4). IEEE.

73. Sajjad, G., Khan, M.B.S., Ghazal, T.M., Saleem, M., Khan, M.F. and Wannous, M., 2023, March. An Early Diagnosis of Brain Tumor Using Fused Transfer Learning. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-5). IEEE.

74.