International Journal of Advanced Biochemistry Research

ISSN Print: 2617-4693
ISSN Online: 2617-4707
IJABR 2024; SP-8(4): 469-478
www.biochemjournal.com
Received: 18-01-2024
Accepted: 21-02-2024

MK Chavan
Ph.D. Scholar, Department of Animal Husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

SA Dhage
Associate Professor, Department of Animal husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

US Gaikwad
Assistant Professor, Department of Animal Husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

DK Deokar
Associate Professor, Department of Animal husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

AT Lokhande
Assistant Professor, Department of Animal Husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

DK Kamble
Head, Department of Animal husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

Corresponding Author:
MK Chavan
Ph.D. Scholar, Department of Animal Husbandry and Dairy Science, Post Graduate Institute, MPKV, Rahuri, Maharashtra, India

Digital livestock farming: A review

MK Chavan, SA Dhage, US Gaikwad, DK Deokar, AT Lokhande and DK Kamble

DOI: https://doi.org/10.33545/26174693.2024.v8.i4Sf.1027

Abstract
This paper explores the growing application of biosensors in animal health management, emphasizing the need for an integrated online monitoring system. As global population increases, the paper highlights the importance of adapting livestock agriculture with Precision Livestock Farming (PLF) technologies, focusing on biometric sensors, big data, and blockchain. Biometric sensors provide real-time health and behaviour data, integrated through big data analytics for population-level insights. Blockchain ensures secure traceability of animal products, addressing concerns about disease outbreaks and enhancing consumer trust. The review discusses the advantages of wearable technologies such as biosensors techniques for detecting infectious diseases in cattle, poultry and swine. While PLF technologies hold promise, challenges like data privacy and technology validation need attention for widespread commercial feasibility.

Keywords: Digital technology, biometric sensors, big data, precision livestock farming, blockchain

1. Introduction

As the global human population increases, upto 2050, the projected global human population is over 9 billion which is approximately 2 billion more than the current population (FAO, 2011) [6]. This population growth occurs primarily in developing countries, India is one of the leading developing country throughout the world. So the development in these countries and increasing population will create an increased demand for animal products. India's total livestock population is 535.78 million which provides stable food sources, employment and opportunities for increased income. Much of the demand for animal products will be met by local production. However, despite the increasing population and demand for animal product, consumers are becoming more aware about the negative impact of livestock farming on the environment, human health, and animal welfare (Ochs D.S. *et al*. 2018) [13]. Land and water will become increasingly competitive resources, meaning livestock producers will become increasingly competitive resources, meaning livestock producers will need to maximize production while employing their limited resources sustainably (Baldi A., *et al*. 2017) [1]. Digitalization will help to achieve these goals. To meet the growing demand for animal protein while addressing concerns about environmental sustainability, human health, and animal welfare, farmers and animal scientists may rely increasingly on PLF, Artificial intelligence, GIS and IoT technologies to digitalize livestock farming. This review paper focuses on various technologies - mainly biometric sensors, big data, and blockchain technology - that can help farmers increase production while addressing environmental sustainability and consumer concerns.

1.1 Recent trends in livestock farming

Over the past ten years, significant advancements have been made in waste management, automated feeding systems, milking robots, and instrumentation, as well as in increasing production efficiency through genetics, animal breeding, and nutrition. Even with these advancements, there are still big problems. To satisfy the growing demand for animal products, intensive livestock management is required; yet, because livestock housing is small and congested, it is challenging for farmers to closely monitor animal health and welfare. As a climate change livestock animals will be more susceptible to illness, heat stress, and other health problems (U. Bernabucci, 2019) [50]. As a result, there will be more pressure to recognize health problems and disease outbreaks early on, comprehend how diseases spread, and take preventative action to stop significant economic losses (S. Neethirajan, 2017) [17]. These problems, as well as escalating concerns over animal welfare, transparency, and environmental sustainability, have led to growing interest in digitalizing livestock farming with PLF, Artificial intelligence, GIS and IoT technologies.

1.1.1 Artificial Intelligence

Artificial Intelligence (AI) technology play vital role in livestock production to solve animal welfare and health related problems, so as to achieve good economic benefits (Figure 1). AI used to solve the main concerns (i.e., costs and disease) and to improve animal production efficiency. AI focus on the quality of animal care as well as the state of animal welfare are considered as the effective ways to achieve an optimal and sustainable livestock farming. To some extent, it is not easy to achieve good animal welfare that covers with various condition of health, safety, behavioral and emotional expression with traditional measures. Fortunately, the emerging AI technology are sought to have the potential to cope with and improve animal welfare for improving production performance in animal farming (Alves *et al*., 2021) [9].

Numerous studies on sensors, data processing and transmission, artificial intelligence (AI) models of machine learning (ML), deep learning (DL), artificial neuro networks (ANN), etc., have been conducted recently in an effort to address issues with animal identification, behavior detection (Riaboff *et al*., 2022) [42], disease monitoring (Vonk *et al*., 2021) [54].

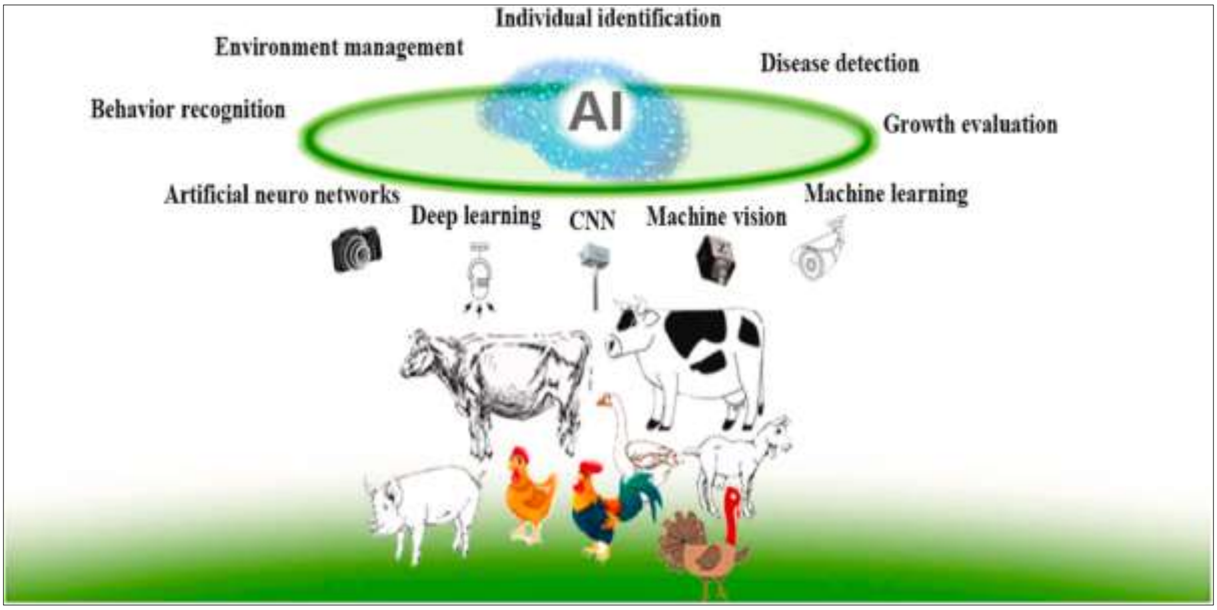

Fig 1: Use of artificial intelligence in livestock farming

1.1.2. Internet of Things (IoT)

The Internet of Things has the potential to revolutionize the livestock farming industry by improving efficiency, reducing costs and increasing productivity. IoT plays an Important role in providing innovative solution to revolutionize the agriculture and farming sectors (Figure 2) (Vijay Rana *et al*. 2023) [41]. Principle of IoT including uniquely determining interconnected devices, extracting the data from sensors and storing it in base station, which is used by machine learning algorithms to achieve advance goals. It also used location monitoring technology to record the movement of animals and indicate signals when they interrupt the boundary of the sensors of the farm and determine the animal health and wellbeing of farm animals (Parisa Niloofar *et al*. 2021) [37].

Traditional farming is changing due to the increasing growth of IoT in livestock farming, which not only makes it more cost-effective but also uses intelligent technology to help farmers reduce crop waste. Important improvements in the last few years include machine-assisted milking, automated feeding, and optimizing production efficiency through nutrition, instrumentation, and animal health monitoring. Significant obstacles still exist in spite of this progress. To meet the increasing demand for animal products, intensive livestock farming is necessary. However, because cattle live in cramped, confined spaces, housing makes it difficult for farmers to closely identify and monitor animal health. These problems prompt the goal of identifying health and disease outbreaks at an early stage, figuring out how diseases spread, and taking preventative measures to avoid huge level economic losses.

1.1.3 Geographical Information System

Spatial analysis and asset mapping play a vital role in livestock farming by providing insights into optimal use of land, resource allocation, and infrastructure planning. By understanding spatial patterns and relationships, farmers can increase productivity, ensure efficient utilization of resource, and improve animal welfare in their operations. GIS offers a comprehensive and reliable solution for generating precise and comprehensive maps of infrastructure in the livestock farming. This includes various livestock production assets such as veterinary hospitals, animal breeding centers, AI centers or semen stations, distribution centers for fodder seeds, pasture lands, livestock markets, cattle fairgrounds, and laboratories for feed analysis, quality control, and disease identification.

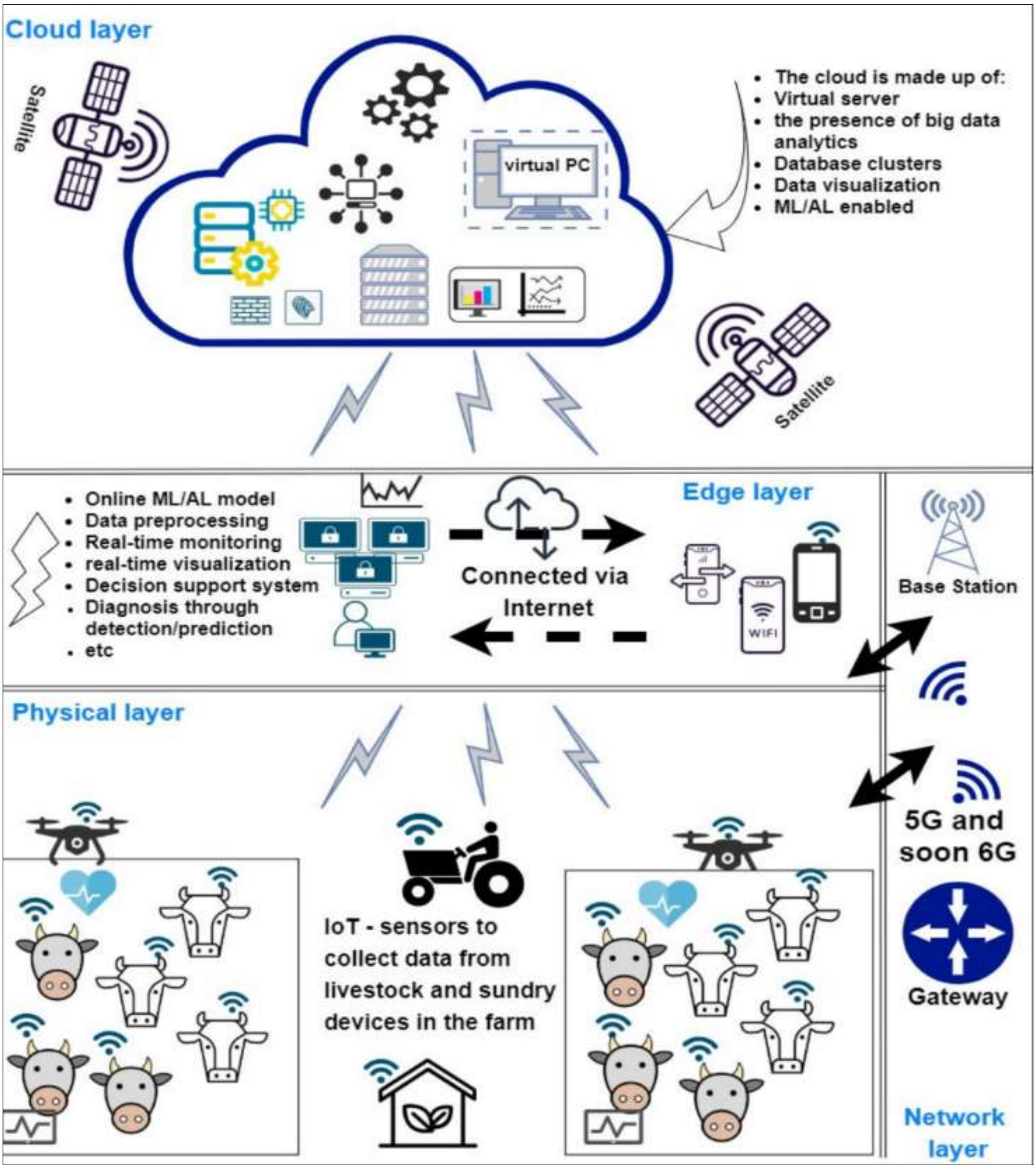

Fig 2: Multi-layer smart Internet of Things (IoT) approach for livestock management (Vijay Rana, 2023) [41]

2. Biometric sensors

Biometric sensors play crucial role in management of animal health. When the biosensors constructed accurately and utilized appropriately, these tools help diagnose animal illnesses quickly, hence reducing financial losses. These are especially helpful for farms that raise poultry and dairy cattle. Reliable data regarding the physical status of the animals can be obtained using on-site sensors, rather than depending exclusively on the farmers' senses and expertise. Owing to their outstanding performance, sensors have the potential to revolutionize livestock growth and are poised to emerge as one of the most significant and useful technologies in the animal health sector (Neethirajan, 2017) [17].

Farmers are able to evaluate an animal's health and welfare over time by using biometric sensors to track the physiological and behavioral characteristics of their livestock (Neethirajan, 2017) [17]. The vast array of biometric sensors that are currently available are both invasive and non-invasive. Surveillance cameras and feed system sensors are examples of non-invasive sensors that can be placed throughout the barn to track animal weight and feed intake. Noninvasive sensors can also be easily affixed on animals, such pedometers, activity sensors based on microelectromechanical systems (MEMS) and the global positioning system (GPS), which can be used to track behavior (Helwatkar *et al.* 2014) [3]. Less frequently researched in cattle, invasive sensors are usually ingested or implanted in animals. These sensors are helpful for tracking internal physiological parameters like body temperature, rumen health, and vaginal pressure in dairy cow.

The livestock sector has adopted the use of biometric sensor technology to give accurate, unbiased measurements of animal health and welfare while monitoring a greater number of animals with fewer personnel and longer contact times (Helwatkar *et al*. 2014, Neethirajan, 2017) [3, 17]. Sensors collect data, which is subsequently analyzed by algorithms sets of instructions or calculations that are carried out in a sequential manner to address certain problems and stored in databases. Biologically relevant information, such as the amount of time animals spend engaging in a given behavior on a given day or the variations in activity level over specified time periods, is obtained through the processing of raw sensor data by specialized algorithms when using livestock biometric sensors (Benjamin and Yik, 2019) [30]. Additionally, these sensors can track animal activities within predetermined parameters and notify farmers when an animal exhibits anomalous behavior, enabling them to check the condition of animal and respond appropriately to improve health and welfare (Neethirajan, 2017) [17]. Combining biometric sensors with big data analytics, artificial intelligence, and bioinformatics technologies, such as those used in genomics, could identify animals with desirable qualities and select them for breeding programs (Ellen E.D. *et al.* 2019) [15].

Over the next ten years, it is expected that the usage of biometric sensors in animal health and livestock production would rise (Neethirajan, 2017) [44]. This is because of their considerable advantages in terms of precision, real-time output, and the volume of data they can gather. Early information gathering about animal wellbeing facilitates early intervention and frequently reduces the need for additional interventions. One non-invasive method of monitoring body temperatures instead of using invasive thermometers that need handling and restraining of animals is thermal infrared (TIR) imaging. In comparison to conventional methods, TIR of the eye region and general skin temperature can monitor stress and diagnose sickness 4-6 days earlier (Koltes J. E. *et al*. 2018) [22]. This allows for quick treatment and reduces the risk that illness will spread throughout flocks. sickness 4-6 days earlier (Koltes J. E. *et al*. 2018) [22]. This allows for quick treatment and reduces the risk that illness will spread throughout flocks. The most widely used non-invasive sensors for tracking livestock animals are radio-frequency identification systems, accelerometers, and thermometers. cameras, microphones, and (RFID) tags. These enable farmers to keep a close watch on the barn's temperature, activity level, noise levels (such as vocalizations, coughing, and sneezing), and particular behaviors such as pig aggression. (Benjamin and Yik, 2019) [30].

Measuring stress in animals before slaughter, thermometers and physiological sensors (e.g., TIR and heart rate monitors) can be compared with meat quality measures to enhance the uniformity and consumer products' quality (Jorquera M. *et al*. 2019) [34]. Researchers may compare individual reactions among animals, measure how the heart rate changes over time in response to various stressors, and detect changes in the heart rate in real time in response to both positive (eustress) and negative stressors with the use of biometric sensors. In a pig investigation, heart rate was raised for one minute after a loud noise due to a negative stressor. A towel to play with served as a positive stressor that also raised heart rate for two minutes after it was given. More traditional or indirect measures of welfare may not be able to detect these subtle differences (Joosen P., *et al*. 2019) [38].

An increasing number of livestock farmers are using RFID devices which can be implanted subcutaneously or attached in ear tags and collars to track a range of behaviors, including general activity, eating, and watering (Neethirajan, 2017) [44]. By employing microphones to record vocalizations and coughs, acoustic analysis can detect welfare concerns in farmers before they increase. The ability to quietly and easily install microphones in barns to keep watch on big herds of animals is another benefit of using them (Mahdavian, *et al*. 2020) [5]. In a similar vein, cameras are simple to install in barns and can record a multitude of useful data. Changes in an animal's posture that could be a sign of lameness or other morbidities can be identified using algorithms for video pictures (Jorquera M., *et al*. 2019) [34]. Analyzing camera images enables tracking of an animal's weight, walk, water intake, unique identity, and aggression (Norton, *et al*. 2019) [49].

Another rapidly expanding field of interest in automated animal welfare monitoring is facial identification technology. Machine learning computer algorithms are used by facial detection technologies to identify individual animals based on their facial traits or to track change related to emotional states (Marsot, *et al.* 2020) [35]. In order to assist stockpeople in properly monitoring animals' affective states, including pain, a number of animal welfare researchers are creating "grimace scales" for animals (Viscardi A. V., *et al*. 2017) [8]. Oftentimes, castration, dehorning, and tail docking are uncomfortable treatments performed on livestock animals (Viscardi A. V., *et al*. 2017) [8]. Animal behavioral intent can be ascertained with sufficient specificity using facial expression analysis. Pigs that initiate violence and those that retreat or avoid it have been observed to have distinct facial characteristics (Camerlink, *et al*. 2018) [19]. Additionally, facial recognition has been suggested as a less expensive substitute for RFID tags for individual animal identification (Marsot, *et al.* 2020) [35].

Every type of livestock has specific needs for welfare as well as particular challenges. As such, farming applications involving biometric sensors or the combination of numerous sensors will always be species-specific. Therefore, it is advantageous to consider the role of biometric sensors in each of the main livestock categories.

2.1 Biometric sensors for cattle

Biometric and biological sensors have made regular husbandry activities easier, improved monitoring of significant welfare problems possible, and provided insightful data for the cattle farm into measures for productivity. While general activity, affective state, estrus detection, and milking behavior are productivity measures that have been researched for automation, mastitis, cystic ovarian disease, lameness, displaced abomasum, and ketosis are welfare concerns that can be improved through the use of biometric sensors (Helwatkar, *et al*. 2014) [3].

Farmers face distinct husbandry challenges while dealing with animal. A herd's total profitability can be influenced by a variety of circumstances, and individual animals represent a valuable investment. Capacity to quantify the accurately timing the onset of the reproductive cycle (estrus) and monitoring the outcomes in real time is crucial for maintaining the health of the herd, while effectively managing nutrition and energy content is necessary to optimize milk yield. There has been special attention in the use of biometric sensors to identify estrus. A recent study by Rottgen, *et al*. (2020) [52] investigated automated detection and identification of a single cow's vocalizations within the herd, with reported sensitivity at 87% and specificity at 94%, as a potentially functional method for monitoring dairy cows. Pedometers have shown some success for dairy cows (Helwatkar, *et al*. 2014, Rottgen, *et al*. 2020) [3, 52].

Dairy cattle need proper nutrition and energy balance in order to produce milk effectively. Non-esterified fatty acid (NEFA) levels that are in the bloodstream suggest a negative energy balance and may be a sign of serious health issues that require prompt attention. Metabolic conditions, high blood levels of NEFA can cause immune system malfunction, decreased milk supply, loss of appetite, reproductive problems, and mammary gland infections. Currently under development, biosensors that measure NEFA could prove to be quite beneficial for dairy farms (Tuteja S. K., *et al*. 2017) [46].

A major health risk for dairy farms is ketosis, which is frequently accompanied by high betahydroxybutyrate (BHBA) levels. Weng *et al*. (2015) [57] created a biosensor sensor based on quantum dots that can detect this. A different strategy was used by Tuteja *et al*. (2017) [48] with 2D BHBA detection in dairy cattle using MoS_2 nanostructure-based electrochemical immunosensors. This approach proved reliable, demonstrated good specificity and sensitivity, and was on par with kits sold in stores. Furthermore, Veerapandian and colleagues (2016) [36].

MooMonitor is a wearable biometric sensor designed to assess dairy cow grazing behavior; thus far, it has shown a strong correlation with conventional techniques for observation (Werner, *et al.* 2019) [21] It has been proved that biometric sensors may monitor cattle's water intake. Using accelerometers and RFID tags, Williams *et al.* (2020) [29] found that animal behavior patterns could be classified with 95% accuracy. Robotic milking systems for dairy calves have demonstrated how sensor technology can replace some animal husbandry activities, thereby granting animals a degree of autonomy. Wearable sensors on the cow are used by robotic milkers to record her dietary requirements and milking habits (Neethirajan, 2017) [44]. In the dairy farming, these milkers are growing in popularity since they enable remote monitoring of cattle health (Klerkx, *et al*. 2019) [27].

Concerns among consumers over the environmental sustainability of livestock production particularly with regard to cattle are growing. One example of a mitigation strategy is the investigation of biometric sensors as a means of tracking methane emissions (Munoz-Tamayo, *et al.* 2019) [40].

2.2 Biometric sensors for poultry farming

The transmission of illness is a serious concern in the production of poultry. Pathogens can spread rapidly between farms and among birds. Additionally, poultry needs much more precise temperature control than the cattle that has been discussed thus far. This is done to support the right conditions for the embryonic development of chicks as well as to maintain the health of adult birds (Andrianov E. A., *et al*. 2019, Phuphanin A., *et al*. 2019) [14, 7]. Poultry farming therefore depends heavily on quick decisions and real-time data analysis two major benefits of the sensor technology employed in PLF.

PLF sensing platforms and components have the capacity to measure temperature in animal habitats and notify farmers when necessary to take appropriate action. Apart from impacting the development of chicken embryos, In broilers, temperature is also the main cause of heat stress (Bloch V., *et al*. 2019) [51]. When compared to implanted temperature loggers, infrared thermometers have been shown to monitor broiler body temperatures with a high degree of precision (Bloch V., *et al*. 2019) [51]. Non-invasive heart rate monitors have been used to track the temperature during incubation (Andrianov E. A., *et al*. 2019) [14] and find circulatory abnormalities in chicken embryos (Khaliduzzaman A., *et al*. 2019) [4]. Farmers may easily monitor the heart rate of embryos using smartphone apps that are compatible with sensors. This enables them to take necessary action to prevent embryo loss during incubation (Phuphanin A., *et al*. 2019) [7] (Figure 3). Similar to swine, one significant way that sensors can offer crucial information regarding the welfare of chickens is through sound analysis.

The vocalizations of chickens may indicate problems with thermal comfort, social growth, sickness, pecking of the feathers, or disruptions (Mahdavian A., *et al*. 2020, Du X., *et al*. 2020) [5, 56]. Hens have a characteristic diurnal pattern for their vocalizations (Du X., *et al.* 2018) [56]. Abnormal diurnal patterns or an increase in vocalizations inside a barn can be utilized to identify stress in hens, particularly stress related to discomfort with the heat (Du X., *et al*. 2020, Du X., *et al*. 2018) [56, 55]. According to recent study, monitoring chicken vocalizations with machine learning is a dependable method of noninvasively monitoring welfare and early warning sign detection (Du X., *et al*. 2020) [56]. It is possible to track the amount of grain that chickens and turkeys (Nasirahmadi A., *et al.* 2020) [6] are getting by analyzing their pecking sounds. One might employ sneeze detection to monitor respiratory illness (Carpentier L., *et al*. 2019) [26].

A research investigation by Liu and colleagues (2020) [28] examined coughing and body condition scores for a group of broiler chickens; vocalizations made when suffering from respiratory disease and reported 93.8% classification accuracy. Studies have shown that voice activity detection algorithms can distinguish between healthy and sick chickens by extracting animal vocalizations from ambient noise (Mahdavian, *et al*, 2020) [5]. Detection accuracy was lower for chickens with respiratory illness than for healthy birds, at 72% and 95% respectively. Two factors that increased errors in sound detection were age and onset of illness. An explanation for the decreased accuracy of vocalizations for sick chickens is that respiratory disease caused abnormal vocalizations.

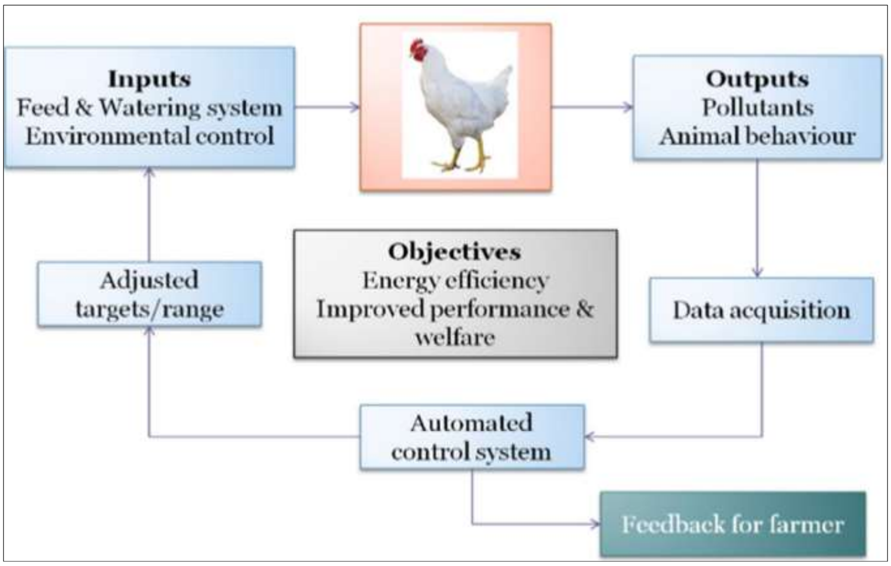

Fig 3: Health indicating parameters and biomarkers measured by biosensors in a Poultry farm (Corkery G., *et al*. 2013) [12]

2.3 Biometric sensors for swine farming

Lameness, hostility in animals kept in groups, physical condition, and health problems like prolapse and disease are some of the major welfare problems in the swine industry. proactive handling of animal, such as Concern over the verification of high welfare standards is growing among both producers and consumers (Buller H., *et al*. 2018) [18] Currently, biometric sensors are being utilized for managing behavioral problems in animals as well as to enhance their health and welfare Currently, 2D and 3D cameras, microphones, accelerometers, radio frequency identification (RFID), thermal imaging, and facial recognition are among the technologies frequently used in swine farming.

Pig vocalizations and coughs can be distinguished from one another using acoustic detection technology (Friel M., *et al.* 2019) [32]. Using sound detection software in a barn would assist farmers in recognizing welfare concerns like hostility, biting of the tail, heat stress, and respiratory infection. Farmers and veterinarians can diagnose respiratory infections up to two weeks ahead of time when using acoustic analysis to detect coughing, as opposed to using sensors alone. Additionally, sound analysis can differentiate between coughs, such as those of pigs suffering from respiratory diseases or those of a healthy pig with mild dust irritation (Norton T., *et al*. 2019) [49].

A pig's unique vocalizations can be used to determine their psychological condition Pigs (Friel M., *et al*. 2019) [32] will scream, for example, when they are in pain or distressed, perhaps from being bit on the tail or ears, or from being crushed in the farrowing crate. Symbols of good health are becoming more and more common as those who care about animals try to give them happy environments instead of just removing painful and stressful situations from their lives. For instance, pigs will bark to warn of impending danger, but they will also do so when they are playing, so this behavior can also be interpreted as a sign of good health (Norton T., *et al*. 2019) [49]. According to Friel *et al*. (2019) [32], pig vocalization duration is a significant predictor of affective state (Friel M., *et al*. 2019) [32] particularly longer grunts, were employed in adverse, whereas shorter duration vocalizations were more common in situations of positive valence.

Aggression among pigs kept in groups is a significant welfare concern in the swine farming. In order to track and manage aggressiveness concerns, researchers are looking into the use of automated video surveillance and tracking of depth imaging. While individual behavioral patterns cannot currently be tracked by these technologies, overall activity patterns may usually be observed (Wurtz K., *et al.* 2019) [25]. Other researchers are using a different strategy to figure out how to act reduce violence, such as figuring out hours of capture of pigs fighting. To effectively interpret violence in videos, automated detection systems and image analysis are being investigated (Norton T., *et al*. 2019) [49]. It is hoped that future studies would combine and integrate thermal imaging and motion tracking to identify hostility and lameness in sows (Benjamin and Yik, 2019) [30].

3. Blockchain Technology

A blockchain is a distributed, decentralized database of encrypted transactions in which every transaction generates a node. Based on agreement from involved parties (peers), these nodes are arranged into records known as "blocks," and blocks are connected by a distinct code. codes, creating a series. Every time a new transaction occurs, a new node is instantly constructed to add to the blockchain with that transaction's information (Chattu, *et al.* 2019) [53]. Blockchain technology is built around four fundamental pillars: freedom, immutability, transparency, and distribution. This implies that in livestock husbandry, each animal on the farm needs to have a special identifier given to it. to collect the data on the farm so it has lived in, the transportation used to convey the animal from the farm(s) to the slaughterhouse.

The detection and tracking of animal disease outbreaks, like the swine flu H1N1, the foot-and-mouth and mad cow diseases in Europe, the avian influenza (Lin J., *et al*. 2018) [20], and the recent rise in salmonella outbreaks (Dyda A., *et al*. 2020) [2], could be significantly assisted by blockchain technology. Additionally, customers are Concerns about the sustainability and morality of livestock farming are growing, and people are calling for transparency in the treatment of animals bred for food. Consumers are also particularly concerned about food safety because, according to the World Health Organization, 1 in 10 people have a disease related to food every year and over 420,000 people pass away.

Fig 5: Livestock supply chain depicting origin, storage, and flow of information as the animal products move from the farm and through processing and distribution channels to consumers (Neethirajan and Kemp, 2021)

4. Big data analytics and machine learning

Large volumes of data are produced when biometric sensors and biosensors are used to monitor the health and welfare of cattle; these data must be processed and evaluated in order to offer insightful information for livestock monitoring. Big data analytics, or the collection and examination of enormous, complicated data sets, has advanced as a result (Wolfert S., *et al*. 2017) [45]. Big data are defined as collections of data that have a lot of variables or predictors, making them messy and unsuitable for standard statistical methods, and a lot of rows and columns, making it impossible to visually evaluate the data (Morota G., *et al.* 2018) [17]. Four essential characteristics, referred to as the "4 Vs" model, define big data: (i) volume, or the amount of data; (ii) velocity, or the rate at which the data is accessed or used; (iii) variety, the different forms of the data; and (iv) veracity, cleaning and editing the data (Wolfert S., *et al.* 2017, Koltes, *et al*. 2019) [45, 23].

It is possible to separate sensor data into two categories: environment-oriented data and animal-oriented (phenotype) data. It is important to monitor these two categories of data at the same time since both impact on the production and wellness of animals. Utilizing data pertaining to animals and the environment to digitalize livestock agriculture has the potential to enhance greenhouse gas emissions, nutrition, genetics, reproduction, welfare, and general health management (Pineiro C., *et al*. 2019) [11].

The implementation of precision livestock farming necessitates the appropriate utilization of big data analytics and modeling to provide management with insights into animal health and welfare concerns related to decreasing productivity trends, reproductive status, and nutritional requirements. Big data models gather data from sensors, interpret it, and look for anomalies in the information that might be influencing the animals. Large-scale data models enhance the effectiveness of sensor technology by filtering through to produce useful output for farms, such as the possibility of predicting future events, enhancing farmer response and decision-making, and possibly even enabling farmers to group animals according to needs, resulting in increased resource utilization (Koltes, *et al.* 2019) [23].

Predictive and exploratory data modeling are the two main categories. Exploratory models utilize data from previous events and determine which factors were influential, whereas predictive models utilize information to forecast future events according to specific standards (Sasaki, 2019) [58]. When utilizing large data sets, proper data modeling is crucial because of the unpredictability in the data, which implies that many variables must be taken into consideration in the models and that noise must be removed from the data by cleaning (Koltes, *et al.* 2019) [23]. Farmers may implement a more proactive management strategy and forecast future results by using predictive models (Wolfert S., *et al.* 2017, Koltes, *et al*. 2019) [45, 23].

The branch of artificial intelligence known as "machine learning" makes use of statistical inference and prediction algorithms (Morota G., *et al*. 2018) [17]. Similar concepts are used in data mining, but the emphasis is on teaching databases to recognize patterns in order to provide information. The use of machine learning (ML) as a Precision livestock farming is becoming more and more interested in big data because it enables computer algorithms to learn from sensor huge data sets and enhance themselves based on that learning, doing away with the need for human data analysts (Benjamin and Yik, 2019) [30].

By establishing contact networks and identifying high-risk people, big data technology can also be effective in tracking the spread of disease (Vanderwaal, *et al*. 2017) [24]. Big data analytical technology prediction models can be utilized to create digital agricultural service systems that may increase the capacity for animal production based on information from biological and biometric sensors. Output as well as the welfare of the animals. For instance, the MooCare predictive model was created to help dairy producers manage dairy farming by predicting milk production through the integration of big data and Internet of Things (IoT) sensors (Rosa Rghi, *et al.* 2019) [39]. Big data sets have been used to create models that have been used to identify and forecast chicken diseases (Gulyaeva, *et al*. 2020) [33]. A digital fingerprint that may be used in predictive and adaptive decision-making models is created by combining digital data from the animals' wearable sensors and livestock husbandry sensing platforms (Figure 6).

In animal genetics research, machine learning (ML) approaches are widely employed for genotyping imputation, outlier detection in populations, and phenotypic prediction based on genotypic information. Also, ML has been applied to image processing to determine body weight, automated milking systems on dairy farms to identify mastitis, and microbiome health monitoring (Morota G., *et al*. 2018) [17].

Big data analytics and machine learning have the potential to raise dairy cattle's health and efficiency. In dairy cattle, they can be used to track and forecast the risk of lameness and mastitis. Circumstances being very urgent welfare concerns that may severely impact milk production (Ebrahimi, *et al*. 2019) [31].

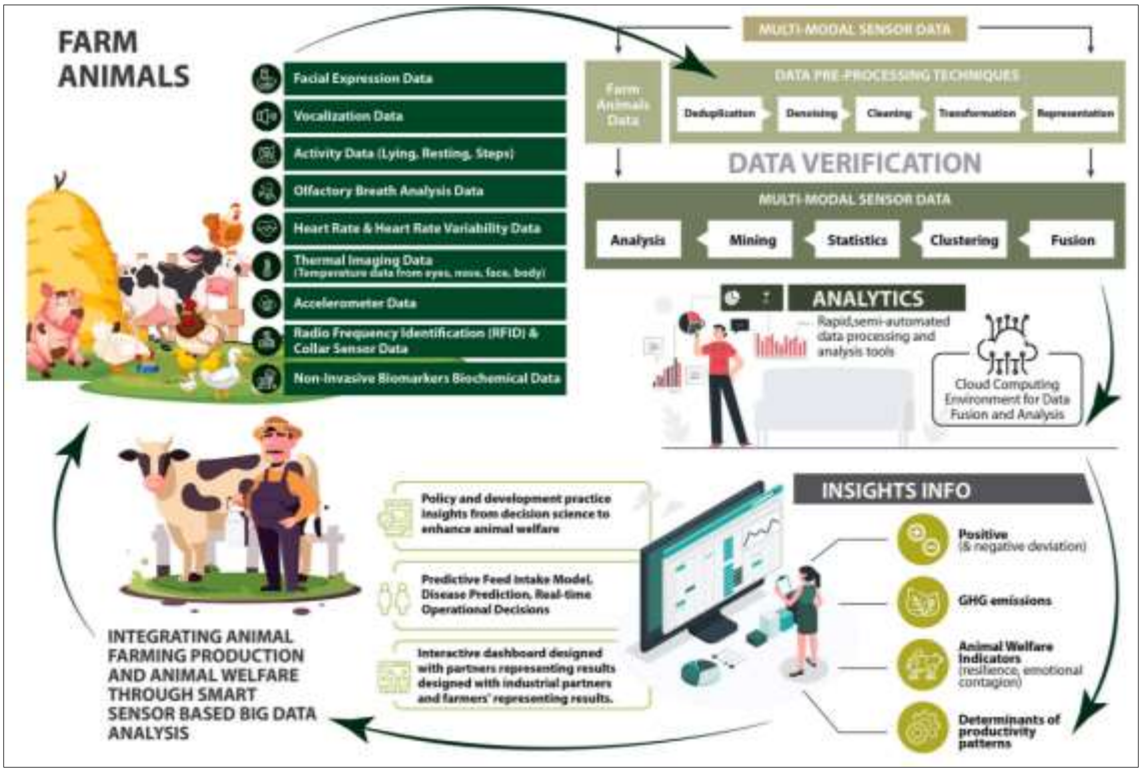

Fig 6: Big Data for Animal Farming (Neethirajan and Kemp, 2021)

5. Conclusion

It may be concluded that recent advancements in precision livestock farming (PLF) technologies have garnered significant attention due to their potential to enhance animal production efficiency while addressing crucial consumer concerns regarding animal welfare, environmental sustainability, and public health. Key components of these technologies include biometric and biological sensors, big data analytics, and blockchain technology. Biometric and biological sensors enable real-time monitoring of animal health and welfare parameters, facilitating proactive management strategies to ensure a sustainable and safe food supply. Big data analytics processes the vast amount of sensor data into actionable insights for farmers, optimizing decision-making processes. Blockchain technology renders livestock agriculture more and more transparent and traceable, increasing consumer trust with improving food safety.

6. References

1. Baldi D, Gottardo A. Livestock Production to Feed the Planet: Animal Protein: A Forecast of Global Demand over the Next Years. Rel: Beyond Anthropocentrism. 2017;5:65. https://doi.org/10.7358/rela-2017-001-bald.
2. Dyda PY, Nguyen A, Chughtai CR, MacIntyre R. Changing epidemiology of Salmonella outbreaks associated with cucumbers and other fruits and vegetables. Global Biosecurity. 2020;1(3). https://doi.org/10.31646/gbio.49.
3. Helwatkar D, Riordan J, Walsh J. Sensor technology for animal health monitoring. In: 8th International Conference on Sensing Technology, Liverpool; c2014. p. 266-271.
4. Khaliduzzaman S, Fujitani A, Kashimori T, Suzuki Y, Ogawa N, Kondo N. A non-invasive diagnosis technique of chick embryonic cardiac arrhythmia using near infrared light. Comput Electron Agric. 2019;158:326-334. https://doi.org/10.1016/j.compag.2019.02.014.
5. Mahdavian S, Minaei C, Yang F, Almasganj S, Rahimi S, Marchetto PM. Ability evaluation of a voice activity detection algorithm in bioacoustics: A case study on poultry calls. Comput Electron Agric. 2020;168:105100. https://doi.org/10.1016/j.compag.2019.105100.
6. Nasirahmadi J, Gonzalez B, Sturm O, Hensel U, Knierim U. Pecking activity detection in group-housed turkeys using acoustic data and a deep learning technique. Biosyst Eng. 2020;194:40-48. https://doi.org/10.1016/j.biosystemseng.2020.03.015.
7. Phuphanin L, Sampanporn B, Sutapun B. Smartphone-Based Device for NonInvasive Heart-Rate

Measurement of Chicken Embryos. Sensors. 2019;19(22):4843. https://doi.org/10.3390/s19224843.
8. Viscardi AV, Hunniford M, Lawlis P, Leach M, Turner PV. Development of a piglet grimace scale to evaluate piglet pain using facial expressions following castration and tail docking: a pilot study. Front Vet Sci. 2017;4:51. https://doi.org/10.3389/fvets.2017.00051.
9. Alves VM, Auerbach SS, Kleinstreuer N, Rooney JP, Muratov EN, Rusyn I, *et al*. Curated data in—trustworthy in silico models out: the impact of data quality on the reliability of artificial intelligence models as alternatives to animal testing. Altern Lab Anim. 2021;49(3):73-82.
10. Müller BR, Soriano VS, Bellio JCB, Molento CFM. Facial expression of pain in Nellore and crossbred beef cattle. J Vet Behav. 2019;34:60-65. https://doi.org/10.1016/j.jveb.2019.07.007.
11. Pineiro J, Morales M, Rodríguez M, Aparicio M, Manzanilla EG, Koketsu Y. Big (pig) data and the internet of the swine things: a new paradigm in the industry. Anim Front. 2019;9(2):6-15. https://doi.org/10.1093/af/vfz002.
12. Corkery G, Ward S, Kenny C, Hemmingway P. Incorporating smart sensing technologies into the poultry industry. J World's Poult Res. 2013;3(4):106-128.
13. Ochs DS, Wolf CA, Widmar NJ, Bir C. Consumer perceptions of egg-laying hen housing systems. Poult Sci. 2018;97(10):3390-3396. https://doi.org/10.3382/ps/pey205.
14. Andrianov EA, Sudakov AN, Andrianov AA, Skolznev NY. Non-invasive monitoring of avian embryo heart rate. J Anim Behav Biometeorol. 2019;7(3):119-122. https://doi.org/10.31893/2318-1265jabb.v7n3p119-122.
15. Ellen ED, Van Der Sluis M, Siegford J, Guzhva O, Toscano MJ, Bennewitz J, *et al*. Review of sensor technologies in animal breeding: Phenotyping behaviors of laying hens to select against feather pecking. Animals. 2019;9(3):108. https://doi.org/10.3390/ani9030108.
16. FAO (Food and Agriculture Organization of the United Nations). World Livestock 2011 - Livestock in Food Security. Rome; c2011. Available from: http://reliefweb.int/sites/reliefweb.int/files/resources/Full%20Report_421.pdf.
17. Morota G, Ventura RV, Silva FF, Koyama M, Fernando SC. Big data analytics and precision animal agriculture symposium: machine learning and data mining advance predictive big data analysis in precision animal agriculture. J Anim Sci. 2018;96(4):1540-1550. https://doi.org/10.1093/jas/sky014.
18. Buller H, Blokhuis P, Jensen P, Keeling L. Towards farm animal welfare and sustainability. Animals. 2018;8(6):81. https://doi.org/10.3390/ani8060081.
19. Camerlink E, Coulange M, Farish M, Baxter EM, Turner SP. Facial expression as a potential measure of both intent and emotion. Sci Rep. 2018;8(1):1-9. https://doi.org/10.1038/s41598-018-35905-3.
20. Lin J, Shen Z, Zhang A, Chai Y. Blockchain and IoT based food traceability for smart agriculture. In: Proceedings of the 3rd International Conference on Crowd Sci. and Eng; 2018. p. 1-6.
21. Werner J, Umstatter C, Leso L, Kennedy E, Geoghegan A, Shalloo L, *et al*. Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows. Animal. 2019;13(9):2070-2079. https://doi.org/10.1017/S1751731118003658.
22. Koltes JE, Koltes DA, Mote BE, Tucker J, Hubbell III DS. Automated collection of heat stress data in livestock: new technologies and opportunities. Transl Anim Sci. 2018;2(3):319-323. https://doi.org/10.1093/tas/txy061.
23. Koltes JE, Cole JB, Clemmens R, Dilger RN, Kramer LM, Lunney JK, *et al*. A vision for development and utilization of high-throughput phenotyping and big data analytics in livestock. Front Genet. 2019;10:1197. https://doi.org/10.3389/fgene.2019.01197.
24. VanderWaal K, Morrison RB, Neuhauser C, Vilalta C, Perez AM. Translating big data into smart data for veterinary epidemiology. Front Vet Sci. 2017;4:110. https://doi.org/10.3389/fvets.2017.00110.
25. Wurtz K, Camerlink I, D'Eath RB, Fernandez AP, Norton T, Steibel J, *et al*. Recording behaviour of indoor-housed farm animals automatically using machine vision technology: A systematic review. PloS one. 2019;14(12):e0226669. https://doi.org/10.1371/journal.pone.0226669.
26. Carpentier L, Vranken E, Berckmans D, Paeshuyse J, Norton T. Development of sound-based poultry health monitoring tool for automated sneeze detection. Comput Electron Agric. 2019;162:573-581. https://doi.org/10.1016/j.compag.2019.05.013.
27. Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS-Wagen J Life Sci. 2019;90:100315. https://doi.org/10.1016/j.njas.2019.100315.
28. Liu L, Li B, Zhao R, Yao W, Shen M, Yang J. A Novel Method for Broiler Abnormal Sound Detection Using WMFCC and HMM. J Sensors. 2020;2985478. https://doi.org/10.1155/2020/2985478.
29. Williams LR, Moore ST, Bishop-Hurley GJ, Swain DL. A sensor-based solution to monitor grazing cattle drinking behaviour and water intake. Comput Electron Agric. 2020;168:105141. https://doi.org/10.1016/j.compag.2019.105141.
30. Benjamin M, Yik S. Precision livestock farming in swine welfare: a review for swine practitioners. Animals. 2019;9(4):133. https://doi.org/10.3390/ani9040133.
31. Ebrahimi M, Mohammadi-Dehcheshmeh M, Ebrahimie E, Petrovski KR. Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep Learning and Gradient-Boosted Trees outperform other models. Comput Biol Med. 2019;114:103456. https://doi.org/10.1016/j.compbiomed.2019.103456.
32. Friel M, Kunc HP, Griffin K, Asher L, Collins LM. Positive and negative contexts predict duration of pig vocalisations. Sci Rep. 2019;9(1):1-7. https://doi.org/10.1038/s41598-019-38514-w.
33. Gulyaeva M, Huettmann F, Shestopalov A, Okamatsu M, Matsuno K, Chu DH, *et al*. Data mining and model-predicting a global disease reservoir for low-pathogenic Avian Influenza (A) in the wider pacific rim using big data sets. Sci Rep. 2020;10(1):1-11. https://doi.org/10.1038/s41598-020-73664-2.

34. Jorquera-Chavez M, Fuentes S, Dunshea FR, Jongman EC, Warner RD. Computer vision and remote sensing to assess physiological responses of cattle to pre-slaughter stress, and its impact on beef quality: A review. Meat Sci. 2019;156:11-22. https://doi.org/10.1016/j.meatsci.2019.05.007.
35. Marsot M, Mei J, Shan X, Ye L, Feng P, Yan X, *et al*. An adaptive pig face recognition approach using Convolutional Neural Networks. Comput Electron Agric. 2020;173:105386. https://doi.org/10.1016/j.compag.2020.105386.
36. Veerapandian M, Hunter R, Neethirajan S. Ruthenium dye sensitized graphene oxide electrode for on-farm rapid detection of beta-hydroxybutyrate. Sens Actuators B Chem. 2016;228:180-184. https://doi.org/10.1016/j.snb.2016.01.028.
37. Niloofar P, Francis DP, Lazarova-Molnar S, Vulpe A, Vochin MC, Suciu G, *et al*. Data-driven decision support in livestock farming for improved animal health, welfare and greenhouse gas emissions: Overview and challenges. Comput Electron Agric. 2021;190:106406.
38. Joosen P, Norton T, Marchant-Forde J, Berckmans D. Animal welfare monitoring by real-time physiological signals. Precision Livestock Farming'19. 2019;337-344.
39. da Rosa Righi R, Goldschmidt G, Kunst R, Deon C, da Costa CA. Towards combining data prediction and internet of things to manage milk production on dairy cows. Comput Electron Agric. 2020;169:105156. https://doi.org/10.1016/j.compag.2019.105156.
40. Munoz-Tamayo R, Agudelo JR, Dewhurst RJ, Miller G, Vernon T, Kettle H. A parsimonious software sensor for estimating the individual dynamic pattern of methane emissions from cattle. Animal. 2019;13(6):1180-1187. https://doi.org/10.1017/S1751731118002550.
41. Rana V, Sharma S, Thakur KK, Pandit A, Mahajan S. Internet of Things in Livestock Farming: Implementation and Challenges. 2023.
42. Riaboff L, Shalloo L, Smeaton AF, Couvreur S, Madouasse A, Keane MT. Predicting livestock behaviour using accelerometers: A systematic review of processing techniques for ruminant behaviour prediction from raw accelerometer data. Comput Electron Agric. 2022;192:106610.
43. Neethirajan S, Ragavan KV, Weng X. Agro-defense: Biosensors for food from healthy crops and animals. Trends Food Sci Technol. 2018;73:25-44. https://doi.org/10.1016/j.tifs.2017.12.005.
44. Neethirajan S. Recent advances in wearable sensors for animal health management. Sens Biosensing Res. 2017;12:15-29. https://doi.org/10.1016/j.sbsr.2016.11.004.
45. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming-a review. Agric Syst. 2017;153:69-80. https://doi.org/10.1016/j.agsy.2017.01.023.
46. Tuteja SK, Neethirajan S. A highly efficient 2D exfoliated metal dichalcogenide for the on-farm rapid monitoring of non-esterified fatty acids. Chem Commun. 2017;53:100002. https://doi.org/10.1039/C7CC04894G.
47. Tuteja SK, Neethirajan S. Exploration of two-dimensional bio-functionalized phosphorene nanosheets (black phosphorous) for label free haptoglobin electroimmunosensing applications. Nanotech. 2018;29(13):135101. https://doi.org/10.1088/1361-6528/aaab15.
48. Tuteja SK, Duffield T, Neethirajan S. Graphene-based multiplexed disposable electrochemical biosensor for rapid on-farm monitoring of NEFA and βHBA dairy biomarkers. J Mater Chem B. 2017;5(33):6930-6940. https://doi.org/10.1039/C7TB01382E.
49. Norton T, Chen C, Larsen MLV, Berckmans D. Precision livestock farming: building 'digital representations' to bring the animals closer to the farmer. Animal. 2019;13(12):3009-3017. https://doi.org/10.1017/S175173111900199X.
50. Bernabucci U. Climate change: impact on livestock and how can we adapt. Animal Frontiers: the Review Magazine of Anim Agri. 2019;9(1):3.
51. Bloch V, Barchilon N, Halachmi I, Druyan S. Automatic broiler temperature measuring by thermal camera. Biosyst Eng; c2019. https://doi.org/10.1016/j.biosystemseng.2019.08.011.
52. Rottgen V, Schon PC, Becker F, Tuchscherer A, Wrenzycki C, Düpjan S, *et al*. Automatic recording of individual oestrus vocalisation in group-housed dairy cattle: development of a cattle call monitor. animal. 2020;14(1):198-205. https://doi.org/10.1017/S1751731119001733.
53. Chattu VK, Nanda A, Chattu SK, Kadri SM, Knight AW. The emerging role of blockchain technology applications in routine disease surveillance systems to strengthen global health security. BDCC. 2019;3(2):25. https://doi.org/10.3390/bdcc3020025.
54. Vonk MC, Walker UA, Volkmann ER, Kreuter M, Johnson SR, Allanore Y. Natural variability in the disease course of SSc-ILD: implications for treatment. European Respiratory Review. 2021;30(159).
55. Du X, Lao F, Teng G. A sound source localisation analytical method for monitoring the abnormal night vocalisations of poultry. Sensors. 2018;18(9):2906. https://doi.org/10.3390/s18092906.
56. Du X, Carpentier L, Teng G, Liu M, Wang C, Norton T. Assessment of laying hens' thermal comfort using sound technology. Sensors. 2020;20(2):473. https://doi.org/10.3390/s20020473.
57. Weng X, Chen L, Neethirajan S, Duffield T. Development of quantum dots-based biosensor towards on-farm detection of subclinical ketosis. Biosens Bioelectron. 2015;72:140-147. https://doi.org/10.1016/j.bios.2015.05.008.
58. Sasaki Y. Detection and prediction of risk factors associated with production losses using production records on commercial pig farms. Food Agricultural Policy Platform Article; c2019. Accessed on June 7, 2020 on: http://ap.fftc.agnet.org/ap_db.php?id=1066.