https://doi.org/10.56556/gssr.v3i3.954
ISSN: 2833-986X

REVIEW ARTICLE

An Overview of Precision Livestock Farming (PLF) Technologies for Digitalizing Animal Husbandry toward Sustainability

Homaira Afroz Himu[1], Asif Raihan[2*]

[1]Department of Veterinary and Animal Sciences, University of Rajshahi, Rajshahi 6205, Bangladesh
[2]National University of Malaysia, Bangi 43600, Selangor, Malaysia

Corresponding Author: Asif Raihan. Email: asifraihan666@gmail.com
Received: 16 July, 2024, Accepted: 25 August, 2024, Published: 27 August, 2024

Abstract
As the global population continues to expand, it is imperative for livestock farming to undergo necessary adaptations in order to effectively address the escalating food demands and enhance productivity. Concurrently, it is imperative to acknowledge and tackle concerns pertaining to animal welfare, environmental sustainability, and public health. The primary aim of the article is to provide a comprehensive examination of the latest advancements in the utilization of biometric devices, big data, and blockchain technology for the purpose of digitizing animal husbandry within the context of Precision Livestock Farming (PLF). Biometric sensors are physiological devices utilized for the purpose of monitoring the health and behavioral patterns of an individual animal. This information can be utilized by farmers to do population-level analysis. Big data analytics solutions employ statistical algorithms to examine extensive and intricate data sets, detecting significant trending patterns and offering advisory recommendations for farmers' decision-making. These systems are designed to interpret and integrate data obtained from biometric sensors. Blockchain technology, when combined with sensors, facilitates the secure and convenient tracking of animal products throughout their journey from the farm to the table. This approach demonstrates efficacy in the surveillance of disease outbreaks, the prevention of economic losses, and the mitigation of food-related health pandemics. The implementation of PLF technology within the livestock industry has the potential to contribute to the attainment of sustainable development.

Keywords: Animal husbandry; Precision livestock farming; Technology; Digitalization; Sustainability

Introduction

According to projections, the global human population is anticipated to surpass 9 billion by the year 2050, indicating a growth of almost 2 billion individuals in comparison to the present population. The primary locus of population growth will be observed in developing nations. According to Raihan and Himu (2023), the increase in population and rapid growth in these countries will result in a significant amplification of the market demand for animal agricultural goods. In developing nations, the production of livestock presents dependable food sources, employment opportunities, and potential for increased cash. A substantial proportion of the market demand for animal products will be met by local production. Furthermore, in light of the growing population and the escalating

need for animal protein, consumers are exhibiting heightened concerns regarding the detrimental impacts of livestock production on the environment, public health, and animal welfare (Ochs et al., 2018). Given the diminishing availability of water and land resources, livestock farmers must devise strategies to enhance output while utilizing their few resources in a sustainable fashion (Baldi & Gottardo, 2017).
Moreover, a notable transformation in societal perspectives, namely among consumers, has further emphasized the imperative for conscientious research and innovation in order to effectively tackle pressing concerns in cattle production through the use of circular and sustainable methodologies (Himu & Raihan, 2023). The process of digitalization is expected to facilitate the progressive achievement of these objectives. The application of digital technologies in livestock farming will provide a thorough examination and accurate understanding of the dynamics and impacts of climate change on the ecology of farm animals (Raihan, 2023a). The successful control and mitigation of novel infectious animal illnesses in transboundary livestock, including those that can be transmitted to people (zoonosis), necessitates the adoption of strategic approaches and optimal methodologies. The process of digitalization has the potential to offer several solutions, including the development of prediction tools targeted at the prevention, mitigation, and preparedness of animal diseases and pandemic situations (Raihan, 2023b).
To effectively meet the growing demand for animal protein and simultaneously tackle concerns related to environmental sustainability, public health, and animal welfare, farmers and animal scientists are increasingly relying on Precision Livestock Farming (PLF) technologies to digitize the entire process of livestock agriculture. The present research investigation examines the application of PLF technologies, encompassing biometric sensors, big data, and blockchain technology, with the aim of augmenting livestock productivity, particularly with regards to improving animal health and well-being. Figure 1 illustrates the application of PLF technology in the context of cattle production.

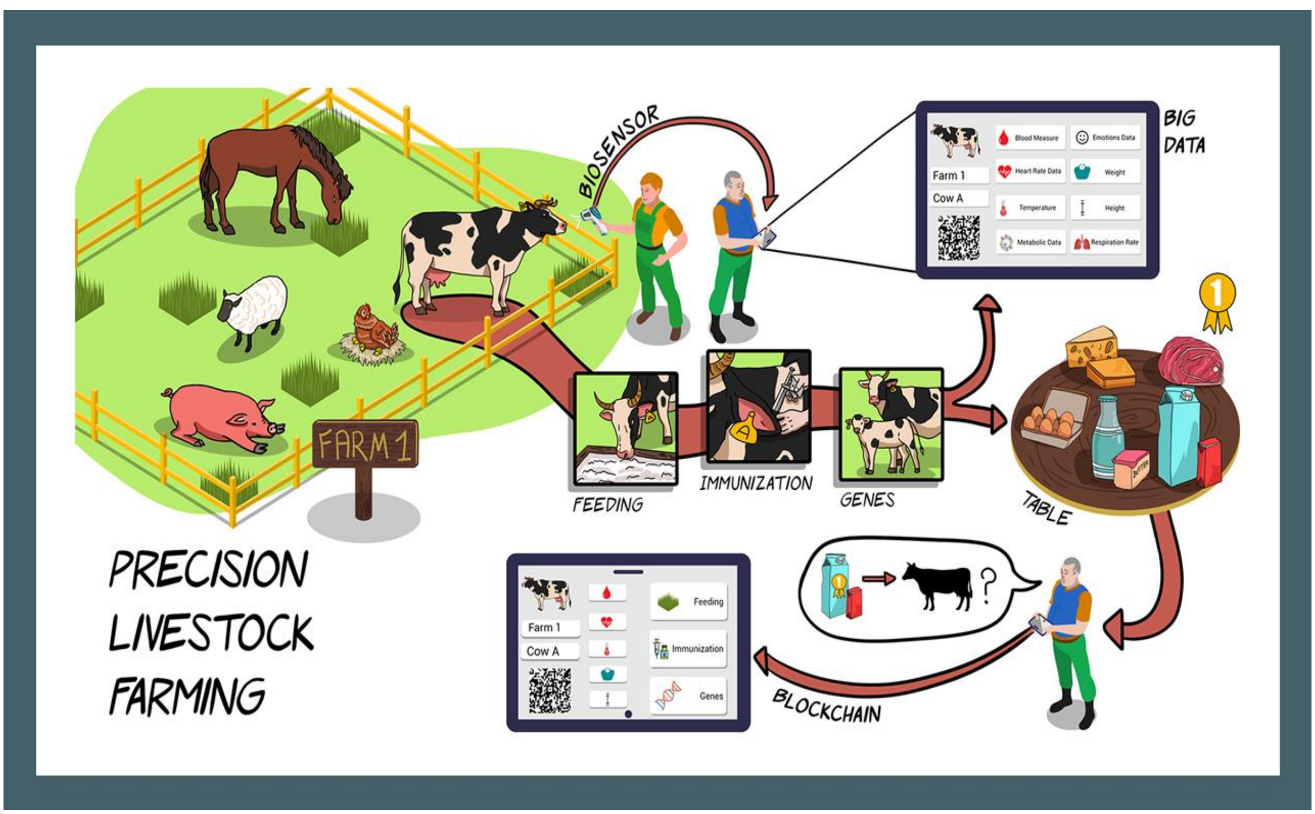

Figure 1. Livestock production with PLF technologies (Neethirajan & Kemp, 2021).

Livestock Farming Trends

In recent years, significant advancements have been achieved in diverse domains, including automated feeding systems, milking robots, waste management, and the enhancement of production efficiency through the utilization of precision instruments, animal breeding techniques, genetic research, and nutritional interventions. Notwithstanding the aforementioned advancements, significant challenges persist. The implementation of intensive livestock management practices is crucial in order to meet the increasing demand for animal products. Nevertheless, the density and overcrowding of livestock housing provide difficulties for farmers in effectively monitoring the animals' health and welfare (Helwatkar et al., 2014). The escalating impacts of climate change are anticipated to heighten the susceptibility of livestock animals to illnesses, heat stress, and various health hazards (Bernabucci, 2019; Raihan, 2023c). As a result, there will be a heightened demand for expeditious identification of health issues and illness outbreaks, comprehension of disease transmission mechanisms, and implementation of preventive measures to alleviate substantial economic repercussions (Thornton, 2010; Raihan, 2023d). In light of growing apprehensions regarding animal welfare, transparency, and environmental sustainability (Raihan, 2023e), there has been a surge in the exploration of digitalizing livestock agriculture through the utilization of PLF technology (Klerkx et al., 2019). The PLF technologies utilize process engineering methodologies to operationalize the automation of livestock agriculture. This technology enables farmers to effectively monitor the welfare and health of extensive animal populations, promptly detect issues with individual animals, and potentially anticipate potential problems through the analysis of historical data (Benjamin & Yik, 2019). Recent advancements in PLF technologies encompass a diverse range of applications. Examples of common applications include the surveillance of bovine behavior, the identification of vocalizations such as screams in pigs, the monitoring of coughs in several animal species to diagnose respiratory ailments, and the detection of bovine pregnancy through alterations in body temperature. The utilization of PLF technology has the potential to assist farmers in the surveillance of infectious illnesses within the realm of livestock agriculture, hence enhancing both food safety and availability. The implementation of PLF technology would ultimately enhance animal welfare and mitigate food safety issues, while simultaneously optimizing resource consumption (Norton et al., 2019).

Livestock Industry Challenges

This study identifies three key factors that provide significant challenges in the efficient monitoring of animal welfare: cost, reliability, and timeliness of observations. A considerable proportion of current techniques are characterized by their time-consuming nature, demanding substantial work and thus, incurring high costs (Jorquera-Chavez et al., 2019). Animal husbandry practitioners often rely on the observations made by stockpeople to detect and address health and welfare concerns. Nevertheless, a considerable disparity exists among commercial establishments in terms of the size of their workforce in relation to the number of animals they house. For example, on a commercial pig farm, the typically observed ratio of stockpersons to pigs is 1:300 (Benjamin & Yik, 2019). Even stockpeople who possess exceptional attentiveness and advanced skills may inadvertently overlook animals in a dangerous condition. Third-party auditing programs offer comprehensive evaluations of animal welfare; yet, they often incur significant costs and consume substantial amounts of time.

The implementation of PLF technologies, specifically biometric sensors, would facilitate the real-time monitoring of animal welfare by farmers, in a manner that is characterized by precision, impartiality, and consistency. This will enable the prompt identification of issues and the timely execution of proactive measures to mitigate significant operational shortcomings. Polymerase chain reaction (PLF) technologies offer a non-invasive sampling method, facilitating the collection of precise data by farmers and researchers. These measurements can then be employed to address welfare concerns (Jorquera-Chavez et al., 2019). Precision farming (PLF) technologies provide the capacity to mitigate resource consumption. The implementation of a proactive and tailored strategy towards animal health has the potential to substantially decrease the dependence on pharmaceutical interventions, particularly antibiotics.

The escalating apprehension among consumers regarding the sustainability and welfare of animal products has resulted in a heightened need for transparency from livestock farmers (Raihan, 2024). The implementation of blockchain technology facilitates the establishment of transparency between farmers and consumers on food offerings, hence alleviating the need for farmers to allocate additional time resources. In the present setting, the time that is conserved could be more efficiently allocated towards the supervision of issues pertaining to animal welfare, public safety, and environmental sustainability (Benjamin & Yik, 2019).

Biometric Sensors

Biometric sensors are utilized to observe and analyze the behavioral and physiological attributes of livestock, hence facilitating comprehensive evaluation of an animal's health and overall welfare by farmers over a specified duration. At present, there exists a wide array of biometric sensors that can be classified into two main categories: non-invasive and invasive designs. One example of versatile non-invasive sensors utilized in barn monitoring encompasses surveillance cameras and sensors integrated into feeding systems, which enable the monitoring of animal weight and feed intake. Non-invasive sensors encompass a range of devices that can be conveniently affixed to animals, such as pedometers, GPS (global positioning system), and MEMS (micro-electromechanical) based activity sensors. These sensors are employed for the purpose of monitoring and mapping animal behavior (Helwatkar et al., 2014). In livestock, invasive sensors are commonly utilized through ingestion or implantation, although their exploration in this context is very infrequent. The utilization of these sensors becomes advantageous in the surveillance of internal physiological parameters in dairy cows, including rumen health, body temperature, and vaginal pressure (Helwatkar et al., 2014). In order to enhance operational efficiency and reduce resource requirements, the livestock industry has adopted biometric sensor technologies to effectively monitor a greater population of animals. The utilization of this approach enables the industry to obtain precise and impartial assessments of animal health and welfare (Helwatkar et al., 2014). The data collected by the sensors is subsequently stored in databases and subjected to analysis using algorithms, which are computational procedures designed to address specific problems in a sequential manner. Real-time livestock biometric sensors employ sophisticated algorithms to interpret unprocessed sensor data and produce biologically meaningful insights. This encompasses quantitative measures such as the average duration of different actions displayed by animals within a particular day, as well as fluctuations in activity levels across specific time intervals (Benjamin & Yik, 2019). Furthermore, these sensors have the capability to monitor behaviors based on predetermined criteria and alert farmers when an animal's behavior deviates from typical patterns. This allows farmers to examine the animal and implement suitable measures to improve its overall health and welfare. The integration of biometric sensors with big data analytics, artificial intelligence, and bioinformatics technologies, including computational genomics, holds promise in identifying animals possessing desired traits and facilitating their inclusion in breeding initiatives (Ellen et al., 2019).

The forecasted trajectory indicates a rise in the utilization of biometric sensors within the livestock farming and animal health sectors over the course of the forthcoming decade. The aforementioned benefits stem from their capability to deliver instantaneous outcomes, exceptional precision, and the aptitude to amass substantial volumes of data. The timely acquisition of information regarding the welfare of animals facilitates prompt intervention and frequently mitigates the necessity for supplementary interventions. Thermal infrared (TIR) imaging presents a viable alternative to invasive thermometers, which necessitate the confinement and regulation of animals, for the purpose of monitoring their body temperatures. The application of thermal infrared imaging (TIR) in the eye area and general skin temperature has demonstrated potential in the early detection of stress levels and diseases, surpassing the capabilities of earlier methodologies, with a typical detection timeframe of 4-6 days (Koltes et al., 2018). The implementation of this approach facilitates prompt intervention and mitigates the potential transmission of diseases among animal populations, such as flocks or herds (Martinez et al., 2020). In the realm of livestock animal monitoring, the primary non-invasive sensors utilized encompass thermometers, accelerometers, radio-frequency identification (RFID) tags, microphones, and cameras. This technological equipment facilitates the ability of farmers to watch and monitor many parameters within the barn, including temperature, activity levels, sound levels (such as vocalizations, sneezing, and coughing), and specific behaviors (such as aggression in pigs) (Benjamin & Yik, 2019).

The utilization of thermometers, in conjunction with physiological sensors such as thermoinfrared (TIR) and heart rate monitors, enables the assessment of stress levels in animals prior to their slaughter. The aforementioned measurements might thereafter be juxtaposed with meat quality indicators in order to enhance the consistency and superiority of consumer products (Jorquera-Chavez et al., 2019). Through the utilization of biometric sensors, researchers are able to promptly detect variations in heart rate pertaining to both positive (eustress) and negative stressors. Additionally, it is possible to do comparisons of individual reactions among animals and see the temporal variations in heart rate resulting from different stressors. In a study using porcine subjects, the introduction of a negative stressor led to a transient elevation in heart rate lasting for a duration of one minute subsequent to the exposure to a high decibel auditory stimulus. The administration of a positive stressor, such as the provision of a towel for play, led to a sustained elevation in heart rate for a duration of two minutes. Conventional or indirect measures of welfare may exhibit limitations in their capacity to detect intricate fluctuations (Joosen et al., 2019). Heart rate monitors are considered to be highly valuable instruments for assessing physiological well-being and the production of metabolic energy. Nie et al. (2020) have demonstrated that biometric sensors, specifically photoplethysmographic sensors, can be conveniently affixed to ear tags or other anatomical regions, enabling uninterrupted monitoring of cardiopulmonary activity in livestock.

There is a growing trend among livestock producers to employ RFID sensors, which can be affixed to ear tags and collars or positioned subcutaneously, for the purpose of monitoring a wide array of behaviors such as general activity, eating patterns, and drinking habits. The application of microphones in acoustic analysis facilitates the monitoring of vocalizations and coughing, hence enabling the timely identification of welfare issues among farmers. Microscopic devices offer the advantage of being easily and inconspicuously deployed within barns for the purpose of monitoring large animal populations (Mahdavian et al., 2020). Likewise, the strategic placement of cameras within barns enables the recording of a wide array of practical data. According to Jorquera-Chavez et al. (2019), computational algorithms designed for video analysis have the capability to detect alterations in the posture of animals, potentially serving as an indicator of lameness and other health conditions. The utilization of camera image analysis facilitates the surveillance of several parameters relevant to animal behavior, including weight, mobility, water consumption, individual identification, and aggression (Norton et al., 2019). The advancement of facial detection technology is becoming a larger priority in the field of automated animal welfare monitoring. The application of machine learning algorithms in facial recognition technologies facilitates the detection of distinct facial traits in animals, hence enabling the recognition of individuals or the monitoring of emotional state fluctuations (Marsot et al., 2020). A cohort of researchers specializing in animal welfare is currently engaged in the advancement of "grimace scales" for various animal species. The primary objective of these scales is to facilitate the reliable monitoring of animals' emotional states, with a specific emphasis on pain (Viscardi et al., 2017). Research has indicated that livestock animals frequently experience stressful procedures, including dehorning, tail docking, and castration (Viscardi et al., 2017; Müller et al., 2019). Accurate identification of behavioral intent in animals can be achieved through the examination of facial expressions. According to Camerlink et al. (2018), pigs exhibiting aggression exhibit distinct facial changes in contrast to those that reduce or refrain from engaging in violent behavior. Previous research has proposed facial detection as a potentially cost-effective alternative to RFID tags for the purpose of identifying individual animals (Marsot et al., 2020).

The utilization of biometric sensors is of paramount importance in the mitigation of disease impacts and transmission. These sensors have the ability to monitor variations in temperature, patterns of behavior, levels of sound, and physiological indications including pH levels, metabolic activity, pathogens, and the identification of toxins or antibiotics within the human body. Presently, the excessive usage of antibiotics in the context of cattle farming represents a noteworthy concern that carries substantial implications for human health (Himu & Raihan, 2023). The capacity to identify the existence of antibiotics empowers farmers to administer healing measures to animals afflicted with ailments, while concurrently guaranteeing the generation of secure and nourishing animal commodities for the global populace. Biologic sensing technologies have the potential to be utilized for the detection and identification of pathogenic infections, such as avian influenza, coronavirus, and Johne's disease. Johne's disease is a pathogenic bacterial infection that exerts detrimental effects on ruminant animals, resulting in substantial economic ramifications for agricultural practitioners. Biometric sensors possess the ability to identify biological markers linked to inflammation, hence facilitating the surveillance of diseases on a significant magnitude. One potential use of thermal infrared imaging (TIR) involves the identification of foot disorders through the analysis of foot pictures (Jorquera-Chavez et al., 2019). Figure 2 illustrates the various applications of biosensors within the context of animal production.

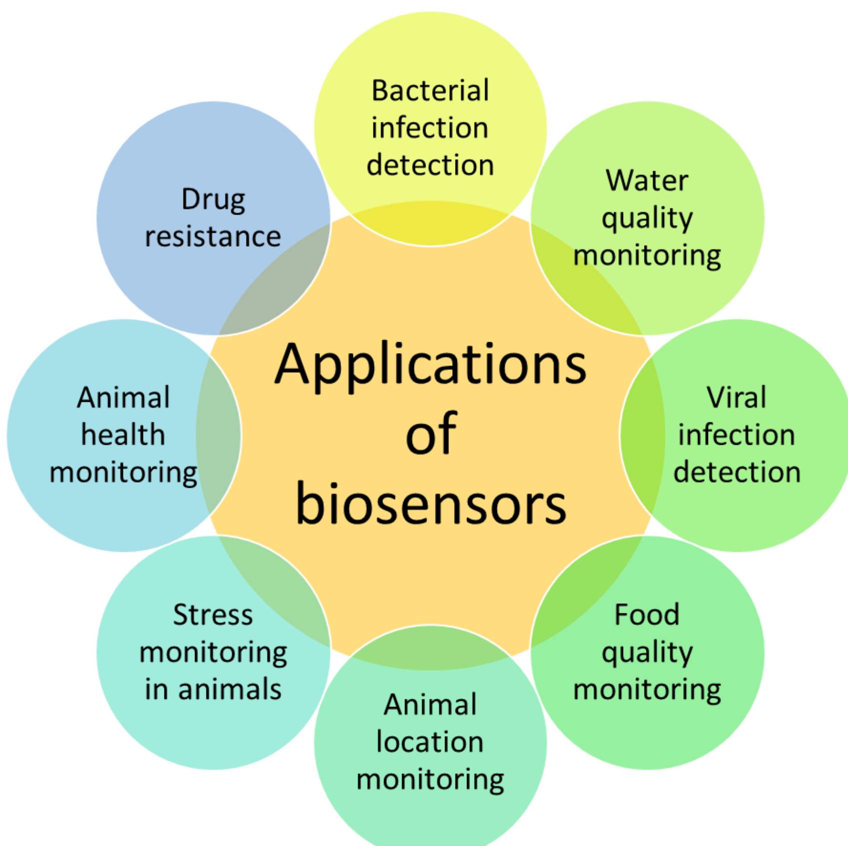

Figure 2. Livestock biosensors applications.

Big Data and Machine Learning

The application of biometric sensors and bioacoustic devices in the surveillance of livestock welfare and health yields substantial volumes of data that necessitate processing and analysis to give valuable insights for animal management. Considerable advancements have been made in the domain of big data analytics, a discipline that encompasses the acquisition and analysis of vast and complex datasets (Wolfert et al., 2017; Raihan, 2023f). The concept of big data pertains to datasets characterized by an extensive quantity of rows and columns, hence posing challenges in terms of visual data analysis. Moreover, the aforementioned data sets sometimes encompass a multitude of variables or predictors, rendering them intricate and unsuitable for conventional statistical methodologies (Morota et al., 2018). The "4 Vs" model, as proposed by Wolfert et al. (2017) and Koltes et al. (2019), encompasses four fundamental attributes that define big data. These attributes include volume, which refers to the numerical quantity of data; velocity, which pertains to the speed at which data is accessed or utilized; variety, which encompasses the diverse forms of data; and veracity, which involves the processes of data cleaning and editing. The utilization of modern data analytics and modeling in PLF technologies enables managers to obtain precise information pertaining to food requirements, reproductive circumstances, and declining productivity trends. This information also serves to identify potential difficulties associated with animal health and welfare. The analysis of data obtained from sensors by big data models enables the identification of irregularities that have the potential to affect animals. The utilization of big data models enhances the efficacy of sensor technology by facilitating the generation of valuable insights for agricultural purposes. These insights encompass the ability to predict the probability of future events, enhance farmer responsiveness and decision-making processes, and potentially enable the categorization of animals according to their specific requirements. Consequently, this facilitates the optimal allocation of resources (Koltes et al., 2019). The data obtained from sensors can be classified into two distinct categories: animal-oriented data, which pertains to the phenotypic features of the animals, and environment-oriented data, which pertains to the characteristics of the surrounding environment. Simultaneous monitoring of both data types is crucial due to their substantial impact on animal health and productivity. The incorporation of animal and environmental data in the adoption of digital technologies in cattle agriculture holds promise for improving multiple facets, including health management, nutrition, genetics, reproduction, welfare, biosecurity, and greenhouse gas emissions (Piñeiro et al., 2019).

The analysis of data can be classified into two primary categories: exploratory and predictive data analysis. Exploratory methodologies involve the examination of historical data in order to find pertinent elements, while predictive models employ data to make projections about future events based on predetermined criteria (Sasaki, 2019). When dealing with extensive data sets, it is imperative to employ precise data analysis techniques. According to Koltes et al. (2019), the inclusion of varied data necessitates the examination of multiple elements within the given situations. Additionally, it is important to eliminate extraneous information in order to cleanse the data systematically. The utilization of predictive approaches by farmers enables them to anticipate future outcomes and implement a proactive management strategy (Wolfert et al., 2017). The application of big data technology has the potential to enhance disease transmission monitoring through the establishment of contact networks and the identification of people with a heightened risk (VanderWaal et al., 2017). Machine learning (ML) is a subfield within the realm of artificial intelligence that employs algorithms to generate statistical predictions and establish conclusions (Morota et al., 2018; Raihan, 2023g). Data mining is a systematic procedure that entails the training of databases to identify patterns and extract relevant information (Raihan, 2023h). Machine Learning (ML) is an emerging domain within the study of PLF that leverages extensive datasets to shape computer algorithms. These algorithms have the capability to continuously gather information from sensor data and enhance their performance autonomously, without the need for human data analysis (Benjamin & Yik, 2019).

Machine learning (ML) techniques are extensively employed in the field of animal genetics research for the purpose of predicting phenotypes based on genotypic data, identifying abnormalities within a population, and performing genotype imputation. The utilization of machine learning (ML) extends to the detection of mastitis in dairy farms through the implementation of automated milking technology, the estimation of body weight using picture analysis, and the monitoring of microbiome health (Morota et al., 2018). Machine learning (ML) and big data analytics have the potential to improve the well-being and efficiency of dairy animal husbandry. The diseases of lameness and mastitis pose substantial welfare concerns in dairy cattle and can exert adverse effects on optimal milk production. Effectively monitoring and accurately anticipating the likelihood of these situations is of utmost importance. The references cited are Ebrahimi et al., 2019; Taneja et al., 2020; Warner et al., 2020.

The application of big data analytics methodologies enables the collection and integration of data from several farms, with the objective of improving the effectiveness of production processes and systems (Aiken et al., 2019). The significance of big data is contingent upon the automation, accessibility, and correctness of the data being considered. In order to uphold the integrity of the data, it is imperative to incorporate error checking and quality control protocols (VanderWaal et al., 2017). In order to optimize the utilization of PLF in agricultural settings, it is imperative to undertake the development of software, implementation of quality control mechanisms, establishment of database systems, and application of statistical approaches to proficiently condense and present the data. Furthermore, it will be imperative to carefully choose the most appropriate data models for this objective (Koltes et al., 2019). The management of extensive data gathered from agricultural operations presents notable obstacles in terms of privacy and security (Wolfert et al., 2017). Consequently, the current utilization of farm data collection is limited due to farmers' overriding concern for privacy preservation. By using data obtained from biometric and biological sensors, sophisticated data analysis techniques can be employed to create digital farming service systems that hold promise for enhancing animal production capacity, productivity, and livestock welfare. The development of the MooCare prediction model aims to assist dairy producers in effectively managing their dairy farming operations through the utilization of Internet of Things (IoT) sensors and big data analytics. The model proposed by Righi et al. (2020) is designed to forecast milk production. In their study, Gulyaeva et al. (2020) developed methodologies utilizing extensive datasets for the purpose of detecting and forecasting chicken diseases. The utilization of wearable sensors and livestock husbandry sensing systems enables the collection of digital data, which can subsequently be employed to develop precise digital fingerprints for animals. The aforementioned fingerprint can then be employed in predictive and adaptive decision-making methodologies. According to Tsay et al. (2019), the three elements, Footprint, Fingerprint, and Forecast, serve as both guiding principles for livestock producers in the management of animal production and as tools for the creation of integrated application systems pertaining to livestock value, supply, and food chains. Figure 3 illustrates the utilization of sensor-based big data applications in the context of precision livestock production.

A blockchain can be defined as a secure and decentralized database of transactions, wherein each transaction is associated with a distinct node (Elisa et al., 2023). The nodes are organized into records, commonly known as "blocks", based on a consensus reached among the participating organizations. The blocks exhibit interconnectivity and include distinct hash codes, so establishing a sequential chain. Upon the occurrence of a new transaction, a node is promptly generated, including pertinent details regarding said transaction, and subsequently appended to the blockchain (Chattu et al., 2019). The core attributes of blockchain technology encompass its distributed nature, transparency, immutability, and democratic underpinnings. Within the realm of livestock management, it is important to assign a distinct identification to every animal present on the farm. The distinct identification will remain associated with the animal throughout its entire lifespan, encompassing data regarding the farm(s) in which it resided, the mode of transportation utilized for transferring the animal from the farm(s) to the slaughterhouse, the veterinarian tasked with examining the animal at the slaughterhouse, the evaluation of quality subsequent to slaughter, the transportation of the meat product, and ultimately, particulars pertaining to the packaging and disposition of the product.

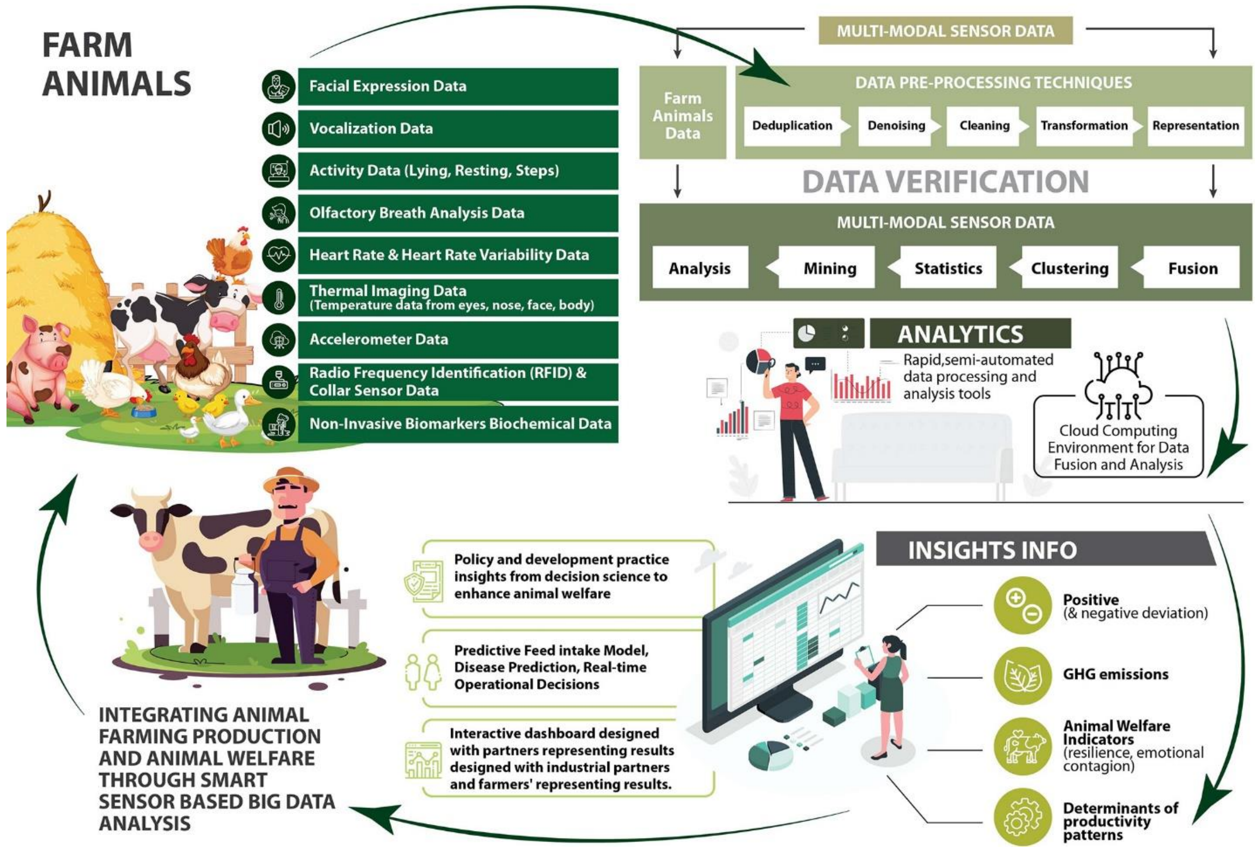

Figure 3. Precision cattle production using sensor-based big data (Neethirajan & Kemp, 2021).

Blockchain

The implementation of blockchain technology in cattle farming presents a multitude of advantages, including the facilitation of decentralized and automated transactions. This has the potential to enhance the effectiveness of auditing systems utilized by certification and regulatory authorities (Akram et al., 2024). Furthermore, it facilitates seamless integration of systems and effectively manages comprehensive documentation of all transactions pertaining to the transportation of animals from their farm to the dining table. Furthermore, it enhances the level of traceability and openness within the cattle farm industry (Picchi et al., 2019). In contemporary times, there has been a growing dearth of trust between farmers and clients due to the escalating demand for transparency in agricultural commodities. The potential of blockchain technology lies in its ability to enhance confidence among consumers through the provision of transparent and comprehensive information pertaining to the complete lifespan of an animal (Patel et al., 2023).

The application of blockchain technology has significant promise in facilitating the detection and surveillance of animal disease outbreaks, encompassing H1N1 swine flu, Foot-and-Mouth and Mad Cow diseases, Avian influenza, and the recent surge in salmonella infections. There is an increasing level of consumer consciousness regarding the environmental and ethical dimensions associated with animal farming (Raihan, 2023i). Furthermore, there is a growing demand for transparency for the methodologies employed in animal husbandry. Ensuring food safety is a significant priority for consumers. Based on data provided by the World Health Organization (WHO, 2020), it is estimated that around 10% of the global population has food-related illnesses each year, leading to an annual mortality rate above 420,000 individuals. The implementation of blockchain technology has promise in enhancing the capacity to monitor and identify the source of hazardous food products, hence enhancing the traceability and accountability for problematic practices within the livestock farming industry (Lin et al., 2018). An essential advantage of blockchain technology is the decentralized distribution of information among a network of users, as opposed to being centralized and managed by a single people or group. In the event of a cattle disease outbreak, producers worldwide would have the ability to securely input and retrieve disease management data. The aforementioned would empower individuals to actively participate in the management of the outbreak or equip themselves for an anticipated outbreak that could impact their agricultural operations (Chattu et al., 2019).

Given the growing globalization of food chains and systems (Raihan, 2023j), it has become imperative for animal products to adhere to various norms and standards pertaining to animal welfare and sustainability. Efficient retrieval of regulatory documentation poses a challenge for regulators and third-party inspectors, particularly when such material is available in physical format or limited databases (Motta et al., 2020). Based on the findings of Motta et al. (2020), it is evident that the cattle farm industry exhibits a relatively lower level of digitalization in comparison to other industries, suggesting a notable opportunity for advancement. The integration of blockchain technology within the realm of animal agriculture has promised in mitigating the aforementioned issues pertaining to disease outbreaks and quality assurance in food production. Depicted in Figure 4 is the streamlined operational framework of the system, which facilitates the provision of services to diverse users. The main objective of the quarantine department is to ensure the comprehensive verification of vaccination quarantines and the meticulous examination of health data information. In contrast, the agricultural regulatory agency is primarily concerned with the specific rules pertaining to the farming process. The environmental protection agency has expressed apprehension regarding the environmental challenges presented during the breeding process, namely pertaining to the management of breeding waste (Raihan, 2023k). However, the main emphasis for farmers lies in acquiring animal breeding genetic data. It is imperative for slaughterhouses to implement a comprehensive system that facilitates the efficient management of livestock slaughter, while distributors necessitate unrestricted access to pertinent slaughter information. In order to conduct precise risk assessments, insurance organizations require comprehensive data regarding the health condition of the authorized livestock, whereas financial institutions prioritize the collection of information pertaining to farmers' assets and livestock breeding techniques.

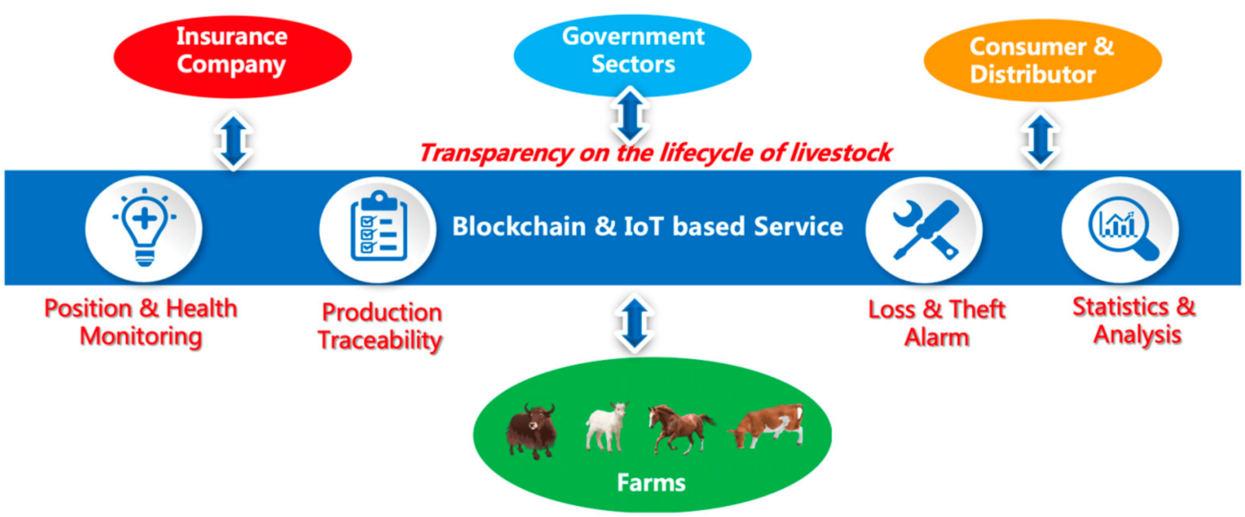

Figure 4. Livestock insurance's streamlined business strategy (Shen et al., 2023).

Notwithstanding its manifold benefits, blockchain technology is now in its nascent stages of advancement for widespread implementation in the food industry, with a restricted body of study investigating its impact on livestock farming (Picchi et al., 2019). Bioengineers and data scientists possess the potential to make substantial contributions towards the establishment of precise criteria for the selection of the most efficient blockchain solution tailored to the unique requirements of various companies within the cattle production sector.

Conclusions

The primary objective of this review article is to examine PLF technologies, which are designed to optimize livestock production while addressing client concerns. The technological approaches investigated in this study encompass biometric sensors, big data analysis, and blockchain technology. The use and integration of PLF technologies have the potential to address the growing apprehensions among consumers pertaining to animal welfare, environmental sustainability, and public health. Furthermore, it can also contribute to addressing the increasing need for animal-derived goods as a result of the growing global population. Biometric sensors facilitate the collection of real-time data pertaining to the welfare and state of animals, thereby empowering farmers to adopt proactive management strategies that promote sustainable and secure food production. Big data analysis is a process that transforms sensor data into valuable and applicable outcomes for agricultural operations. The utilization of blockchain technology in animal husbandry serves to augment transparency and traceability, hence fostering heightened customer confidence and enhancing food safety measures. Nevertheless, the application of PLF technology in animal agriculture is presently in its nascent phase, necessitating the resolution of various obstacles prior to the widespread adoption of these technologies by farmers and consumers on a global scale. The realization of a society that is both digitally inclusive and robust, facilitated by the implementation of novel digitalization methods in cattle farming, necessitates the active involvement and engagement of citizens in the collaborative process and endorsement of technical advancements.

Declaration

Acknowledgment: N/A

Funding: This research received no funding.

Conflict of interest: The authors declare no conflict of interest.

Ethics approval/declaration: N/A

Consent to participate: N/A

Consent for publication: N/A

Data availability: N/A

Authors contribution: Homaira Afroz Himu and Asif Raihan contributed to conceptualization, visualization, methodology, reviewing literature, extracting information, synthesize, and manuscript writing.

References

Aiken, V. C. F., Dórea, J. R. R., Acedo, J. S., de Sousa, F. G., Dias, F. G., & de Magalhães Rosa, G. J. (2019). Record linkage for farm-level data analytics: Comparison of deterministic, stochastic and machine learning methods. *Computers and Electronics in Agriculture*, *163*, 104857.

Akram, M. W., Akram, N., Shahzad, F., Rehman, K. U., & Andleeb, S. (2024). Blockchain technology in a crisis: Advantages, challenges, and lessons learned for enhancing food supply chains during the COVID-19 pandemic. *Journal of Cleaner Production, 434*, 140034.

Baldi, A., & Gottardo, D. (2017). Livestock production to feed the planet: Animal protein: A forecast of global demand over the next years. *Rel.: Beyond Anthropocentrism*, *5*, 65.

Benjamin, M., & Yik, S. (2019). Precision livestock farming in swine welfare: a review for swine practitioners. *Animals*, *9*(4), 133.

Bernabucci, U. (2019). Climate change: impact on livestock and how can we adapt. *Animal Frontiers*, *9*(1), 3-5.

Camerlink, I., Coulange, E., Farish, M., Baxter, E. M., & Turner, S. P. (2018). Facial expression as a potential measure of both intent and emotion. *Scientific reports*, *8*(1), 17602.

Chattu, V. K., Nanda, A., Chattu, S. K., Kadri, S. M., & Knight, A. W. (2019). The emerging role of blockchain technology applications in routine disease surveillance systems to strengthen global health security. *Big Data and Cognitive Computing*, *3*(2), 25.

Ebrahimi, M., Mohammadi-Dehcheshmeh, M., Ebrahimie, E., & Petrovski, K. R. (2019). Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep Learning and Gradient-Boosted Trees outperform other models. *Computers in biology and medicine*, *114*, 103456.

Elisa, N., Yang, L., Chao, F., & Cao, Y. (2023). A framework of blockchain-based secure and privacy-preserving E-government system. *Wireless Networks, 29*(3), 1005-1015.

Ellen, E. D., Van Der Sluis, M., Siegford, J., Guzhva, O., Toscano, M. J., Bennewitz, J., ... & Rodenburg, T. B. (2019). Review of sensor technologies in animal breeding: phenotyping behaviors of laying hens to select against feather pecking. *Animals*, *9*(3), 108.

Gulyaeva, M., Huettmann, F., Shestopalov, A., Okamatsu, M., Matsuno, K., Chu, D. H., ... & Bortz, E. (2020). Data mining and model-predicting a global disease reservoir for low-pathogenic Avian Influenza (AI) in the wider pacific rim using big data sets. *Scientific reports*, *10*(1), 16817.

Helwatkar, A., Riordan, D., & Walsh, J. (2014). Sensor technology for animal health monitoring. *International Journal on Smart Sensing and Intelligent Systems*, *7*(5), 1-6.

Himu, H. A., & Raihan, A. (2023). A review of the effects of intensive poultry production on the environment and human health. *Journal of Veterinary Science and Animal Husbandry, 11*(2), 203.

Joosen, P., Norton, T., Marchant-Forde, J., & Berckmans, D. (2019). Animal welfare monitoring by real-time physiological signals. *Precision Livestock Farming'19*, 337-344.

Jorquera-Chavez, M., Fuentes, S., Dunshea, F. R., Jongman, E. C., & Warner, R. D. (2019). Computer vision and remote sensing to assess physiological responses of cattle to pre-slaughter stress, and its impact on beef quality: A review. *Meat science*, *156*, 11-22.

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen journal of life sciences*, *90*, 100315.

Koltes, J. E., Cole, J. B., Clemmens, R., Dilger, R. N., Kramer, L. M., Lunney, J. K., ... & Reecy, J. M. (2019). A vision for development and utilization of high-throughput phenotyping and big data analytics in livestock. *Frontiers in genetics*, *10*, 1197.

Koltes, J. E., Koltes, D. A., Mote, B. E., Tucker, J., & Hubbell III, D. S. (2018). Automated collection of heat stress data in livestock: new technologies and opportunities. *Translational Animal Science*, *2*(3), 319-323.

Lin, J., Shen, Z., Zhang, A., & Chai, Y. (2018). Blockchain and IoT based food traceability for smart agriculture. In *Proceedings of the 3rd international conference on crowd science and engineering* (pp. 1-6).

Mahdavian, A., Minaei, S., Yang, C., Almasganj, F., Rahimi, S., & Marchetto, P. M. (2020). Ability evaluation of a voice activity detection algorithm in bioacoustics: A case study on poultry calls. *Computers and electronics in agriculture*, *168*, 105100.

Marsot, M., Mei, J., Shan, X., Ye, L., Feng, P., Yan, X., ... & Zhao, Y. (2020). An adaptive pig face recognition approach using Convolutional Neural Networks. *computers and Electronics in Agriculture*, *173*, 105386.

Martinez, B., Reaser, J. K., Dehgan, A., Zamft, B., Baisch, D., McCormick, C., ... & Selbe, S. (2020). Technology innovation: advancing capacities for the early detection of and rapid response to invasive species. *Biological Invasions*, *22*(1), 75-100.

Morota, G., Ventura, R. V., Silva, F. F., Koyama, M., & Fernando, S. C. (2018). Big data analytics and precision animal agriculture symposium: Machine learning and data mining advance predictive big data analysis in precision animal agriculture. *Journal of animal science*, *96*(4), 1540-1550.

Motta, G. A., Tekinerdogan, B., & Athanasiadis, I. N. (2020). Blockchain applications in the agri-food domain: the first wave. *Frontiers in Blockchain*, *3*, 6.

Müller, B. R., Soriano, V. S., Bellio, J. C. B., & Molento, C. F. M. (2019). Facial expression of pain in Nellore and crossbred beef cattle. *Journal of Veterinary Behavior*, *34*, 60-65.

Neethirajan, S., & Kemp, B. (2021). Digital livestock farming. *Sensing and Bio-Sensing Research, 32*, 100408.

Nie, L., Berckmans, D., Wang, C., & Li, B. (2020). Is continuous heart rate monitoring of livestock a dream or is it realistic? A review. *Sensors*, *20*(8), 2291.

Norton, T., Chen, C., Larsen, M. L. V., & Berckmans, D. (2019). Precision livestock farming: Building 'digital representations' to bring the animals closer to the farmer. *Animal*, *13*(12), 3009-3017.

Ochs, D. S., Wolf, C. A., Widmar, N. J., & Bir, C. (2018). Consumer perceptions of egg-laying hen housing systems. *Poultry Science*, *97*(10), 3390-3396.

Patel, A. S., Brahmbhatt, M. N., Bariya, A. R., Nayak, J. B., & Singh, V. K. (2023). Blockchain technology in food safety and traceability concern to livestock products. *Heliyon, 9*(6), e16526.

Picchi, V. V., de Castro, E. F., Marino, F. C., & Ribeiro, S. L. (2019). Increasing the confidence of the Brazilian livestock production chain using Blockchain. In *Proceedings of the 2019 2nd International Conference on Blockchain Technology and Applications* (pp. 93-98).

Piñeiro, C., Morales, J., Rodríguez, M., Aparicio, M., Manzanilla, E. G., & Koketsu, Y. (2019). Big (pig) data and the internet of the swine things: a new paradigm in the industry. *Animal frontiers*, *9*(2), 6-15.

Raihan, A. (2023a). The influence of meat consumption on greenhouse gas emissions in Argentina. *Resources, Conservation & Recycling Advances,* 19, 200183.

Raihan, A. (2023b). An econometric assessment of the relationship between meat consumption and greenhouse gas emissions in the United States. *Environmental Processes*, 10(2), 32.

Raihan, A. (2023c). A review of the global climate change impacts, adaptation strategies, and mitigation options in the socio-economic and environmental sectors. *Journal of Environmental Science and Economics*, 2(3), 36-58.

Raihan, A. (2023d). An econometric evaluation of the effects of economic growth, energy use, and agricultural value added on carbon dioxide emissions in Vietnam. *Asia-Pacific Journal of Regional Science*, 7, 665-696.

Raihan, A. (2023e). Toward sustainable and green development in Chile: dynamic influences of carbon emission reduction variables. *Innovation and Green Development*, 2, 100038.

Raihan, A. (2023f). An Overview of the Implications of Artificial Intelligence (AI) in Sixth Generation (6G) Communication Network. Research Briefs on Information and Communication Technology Evolution, 9, 120-146.

Raihan, A. (2023g). A comprehensive review of artificial intelligence and machine learning applications in energy consumption and production. *Journal of Technology Innovations and Energy*, 2(4), 1-26.

Raihan, A. (2023h). A Comprehensive Review of the Recent Advancement in Integrating Deep Learning with Geographic Information Systems. Research Briefs on Information and Communication Technology Evolution, 9, 98-115.

Raihan, A. (2023i). The dynamic nexus between economic growth, renewable energy use, urbanization, industrialization, tourism, agricultural productivity, forest area, and carbon dioxide emissions in the Philippines. *Energy Nexus,* 9, 100180.

Raihan, A. (2023j). Sustainable development in Europe: A review of the forestry sector's social, environmental, and economic dynamics. *Global Sustainability Research,* 2(3), 72-92.

Raihan, A. (2023k). Economy-energy-environment nexus: the role of information and communication technology towards green development in Malaysia. *Innovation and Green Development*, 2, 100085.

Raihan, A. (2024). The influence of tourism on the road to achieving carbon neutrality and environmental sustainability in Malaysia: the role of renewable energy. Sustainability Analytics and Modeling, 4, 100028.

Raihan, A., & Himu, H. A. (2023). Global impact of COVID-19 on the sustainability of livestock production. *Global Sustainability Research*, 2(2), 1-11.

Righi, R. R., Goldschmidt, G., Kunst, R., Deon, C., & da Costa, C. A. (2020). Towards combining data prediction and internet of things to manage milk production on dairy cows. *Computers and Electronics in Agriculture*, *169*, 105156.

Shen, L., Zhang, Z., Zhou, Y., & Xu, Y. (2023). Applying Blockchain Technology and the Internet of Things to Improve the Data Reliability for Livestock Insurance. *Sensors, 23*(14), 6290.

Sasaki, Y. (2019). Detection and Prediction of Risk Factors Associated with Production Losses Using Production Records on Commercial Pig Farms. FFTC Agricultural Policy Platform (FFTC-AP).

Taneja, M., Byabazaire, J., Jalodia, N., Davy, A., Olariu, C., & Malone, P. (2020). Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. *Computers and Electronics in Agriculture*, *171*, 105286.

Thornton, P. K. (2010). Livestock production: recent trends, future prospects. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1554), 2853-2867.

Tsay, J. R., Lu, C. T., & Tu, T. C. (2019). Application of common information platform to foster data-driven agriculture in Taiwan. *Food Agricultural Policy Platform Article*.

VanderWaal, K., Morrison, R. B., Neuhauser, C., Vilalta, C., & Perez, A. M. (2017). Translating big data into smart data for veterinary epidemiology. *Frontiers in veterinary science*, *4*, 110.

Viscardi, A. V., Hunniford, M., Lawlis, P., Leach, M., & Turner, P. V. (2017). Development of a piglet grimace scale to evaluate piglet pain using facial expressions following castration and tail docking: a pilot study. *Frontiers in veterinary science*, *4*, 51.

Warner, D., Vasseur, E., Lefebvre, D. M., & Lacroix, R. (2020). A machine learning based decision aid for lameness in dairy herds using farm-based records. *Computers and electronics in agriculture*, *169*, 105193.

WHO. (2020). Food Safety, World Health Organization (WHO). Available at: https://www.who.int/news-room/fact-sheets/detail/food-safety (Accessed 12 December, 2023).

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming–a review. *Agricultural systems*, *153*, 69-80.