Review of Farmer-Centered AI Systems Technologies in Livestock Operations

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Abstract

The assessment of livestock welfare aids in keeping an eye on the health, physiology and environment of the animals in order to prevent deterioration, detect injuries, stress, and sustain productivity. Because it puts more consumer pressure on farming industries to change how animals are treated to make them more humane, it has also grown to be a significant marketing tactic. Common visual welfare procedures followed by experts and vets could be expensive, subjective, and need for specialized staff. Recent developments in artificial intelligence (AI) integrated with farmers expertise have aided in the creation of novel and cutting-edge livestock biometrics technologies that extract important physiological data linked to animal welfare. A thorough examination of physiological, behavioral, and health variables that highlights AI's ability to provide accurate, rapid, and impartial assessments. Farmer-focused strategy: an emphasis on the crucial role that farmers play in the skillful adoption and prudent application of AI and sensor technologies, as well as conversations about developing logical, practical, and affordable solutions that are specific to the needs of farmers.

1. Introduction

Regardless of the inventive changes and improvements that Artificial Intelligence (AI) introduction would bring to livestock farming, there is a need for farmers to be integrated into the process of achieving an optimized livestock operation, as AI systems cannot observe and effect required changes in livestock. Hence, there is a need to ensure farmers are being considered in the optimization of livestock operations with AI systems (Rezvanfar., 2007).

However, the present measures of livestock farming include the examination of livestock health, physiology, and behavior being carried out manually. The use of sensor technology in livestock production is expanding as a means of enhancing animal welfare, productivity, environmental impact reduction, and traceability. Information such as animals' behavior, feed intake, and water use can all be tracked using AI systems, which can also be used to evaluate environmental conditions (Olejnik et al., 2022). Feeding and breeding procedures can be improved by using AI systems to monitor animals' water and feed intake. Using this data, livestock farmers may check if animals are receiving the nutrients they require and spot animals that are not reproducing successfully. Lessening the impact on the environment: These systems can be used to manage and monitor the energy and water use in cattle operations, observation of welfare and health of animals' activity level, heart rate, respiration rate, and body temperature. The potential data would serve as an information that will be useful to spot early indications of stress or disease, the security and safety of food can also be improved using this information (Ezanno et al., 2021), theses systems can be used to track the movement of animals and the goods they produce, hence improving traceability (Dineva et al., 2021). It is possible to use this data to pinpoint places where efficiency could be increased.

Livestock operations undoubtedly contribute significantly to state economic development, as they provide raw materials for fertilizers products and dairy industry. Hence, there is a need for state involvement in the effective planning and implementation of systems that would help optimize production of livestock products as purchasing AI systems that would help achieve this could be too expensive for livestock farmers to implement, however there might also be some caution to be taken by the farmers that would need the state officials to serve as a regulating body (Olumide et al., 2023).

An increasing number of advanced tools are now available to farmers due to the rapid growth of technology in agriculture. However, this does not mean these technologies will be used effectively just because they exist, as the farmer's perspective is essential to the successful adoption and use of technology in agriculture (Wang and Capareda, 2020). With integration of farmers in AI systems for animal livestock optimization, the farmer is considered as the major stakeholder and their special knowledge, demands, and challenges are acknowledged and included into the process of development and implementation of AI technologies. Fundamentally, a farmer-centric approach respects the knowledge and expertise of farmers, realizing that no technology can equal their in-depth familiarity with the animals and respective surroundings.

In view of this, it is crucial to develop technology that meet farmers' practical requirements and optimize their capacities rather than trying to replace them (Lioutas et al., 2021). Hence, this study aims to discuss and present the possibility and vast potential in the adoption of Farmer Centered Artificial Intelligent technologies in livestock operations.

Review Methodology: We accessed our review data by searching and combining major databases such as Google Scholar and ScienceDirect. Additionally, we narrowed down our keyword terms to Livestock Welfare Assessment, Precision Livestock Farming, and Animal Welfare Monitoring. We used the references from the articles collected using this procedure to check for further relevant material.

2 AI Systems Technologies in Livestock Operations

This section presents related works that have been carried out in application of sensor technologies in livestock farming. So, for the stakeholders, early use of AI technology in farming will be a fantastic opportunity. This article discusses the AI innovations being applied to animal livestock and the benefits of adopting such technology are also covered in this section.

2.1 AI System for Livestock Behavioural detection and Physiological Monitoring

Oczak et al (2014) study tested a multilayer feed forward neural network and an activity features technique for automatically detecting aggressive behavior in pigs. Eleven male pigs, weighing an average of 23 kg, were used in the experiment. The pigs were videotaped for examination over the first three days following mixing. During the entire 8 hours or 28,800 second video recording, 643 seconds were classified as high aggression incidents and 1253 seconds as medium aggression events. Using software that computed an activity's features or characteristics, the animals' level of activity was monitored during the films. Using the recorded activity, the five features (average, maximum, minimum, total, and variance) were computed over a period of 14 times intervals. The training and validation of a multilayer feed forward neural network was used to categorize episodes of high and medium hostility. The authors examined seven types of artificial neural network (ANN) topologies. The findings showed that ANNs were able to classify high aggression events with a sensitivity of 96.1%, specificity of 94.2%, and accuracy of 99.8% when fed 70 features of the activity index (5 features × 14 intervals) calculated on 241 s time intervals. On the other hand, medium aggression events were classified with a sensitivity of 86.8%, specificity of 94.5%, and accuracy of 99.2%.

Wagner et al (2020) study revealed that sick behaviour features in animals are characterized by decreased activity, increase in sleep, decrease in feed and water intake, occasional waking periods, and decreased environmental interaction. A disease's subtle behavioral changes may manifest just prior to its outward manifestation. Though it is now possible to continuously monitor animal behavior because of sensor advancements, it can still be challenging to identify when an animal is acting abnormally. The study investigated the use of machine learning (ML) to continuous monitoring data in order to identify aberrant behavior. The study subjected 14 bovines (Bos taurus) to Sub-Acute Ruminal Acidosis (SARA), a condition recognized for its ability to cause alterations in behavior. Fourteen more control cows were not included in the SARA. In order to track pH and identify whether a cow had SARA, the study used a ruminal bolus. By using a positioning system, the study was able to determine an animal's activity level based on where it was in relation to other parts of the barn, such as the feeding area, resting area, and lanes. Several machine learning techniques were tried, including K Nearest Neighbors for Regression (KNNR), Decision Tree for Regression (DTR), MultiLayer Perceptron (MLP), Long Short-Term Memory (LSTM), and an algorithm that relies on the assumption of daily activity similarity. First, using data from the preceding 24 hours, machine learning models was created to forecast activity on a given day for the entire cow population. Next, for a certain cow, the study computed the error between observed and expected values. With 83% of SARA cases (true- positives) detected, KNNR performed best; however, it also generated 66% of false-positives, which restricts its practical usage. Finally, machine learning can assist in identifying atypical behavior. Applying machine learning to extremely big datasets at the animal level as opposed to the group level is likely to yield even greater benefits.

Brown et al. (2013) elucidate on the use of devices such as cameras, microphones, and accelerometers being frequently used to record animal behavior. To keep track of the animal activities, this device is mounted on the top or corner of the farm. Using software like Python, and with smart and intelligent models, the data collected from the devices is converted into a useful information system. This monitoring method lessens the workload for farm staff while maintaining the wellbeing and health of the animals.

Li et al. (2020) discussed that Precision Livestock (PLF) systems ought to be used in individual welfare assessments, as the average group welfare level might not be a reliable indicator of a given individual's welfare. Recognizing and tracking animals is necessary while observing individual behavior, particularly when observing numerous individuals in a large group. In PLF systems, radio-frequency identification technology has been used to monitor, identify, and register animals in order to reliably, automatically, and affordably detect behavior and welfare. The RFID technology can gather a lot of data, but it tracks livestock's positions indirectly in order to estimate behavior. Furthermore, the quantity of transponders worn by the hens and the number of mounted antennae affect the precision and tracking of this system. It is therefore impractical to expect every bird on a commercial farm to wear an RFID tag due to their large numbers. Usually, a tagged sample of birds is chosen at random. While hundreds of hens can be equipped with RFID systems, the process of fitting and recycling tags is a tedious and time-consuming task. Target tracking and detection can be accomplished with image processing technologies.

Mancuso et al. (2023) opined that animal welfare and health are enhanced by a deeper comprehension of the relationships that exist between them and their surroundings and how those relationships affect their behavior. Alterations in behavior can also serve as precursors to disease, injury, or environmental issues. Therefore, it is essential to accurately identify these behaviors in order to guarantee excellent monitoring quality, which influences farm decision-making. To categorize behaviors, machine learning techniques have been employed by numerous researchers; nevertheless, feature extraction is a prerequisite. The ability to automatically extract features is one of the advantages of Convolutional Neural Networks (CNN). Also, classifier methods based on Deep Learning (DL) frequently offer higher accuracy than machine learning (ML).

2.2 AI System for Livestock Environmental Monitoring

Adebayo et al (2023) study revealed inadequate methods for early detection and the management of infectious diseases in chicken farms may fail to halt diminishing productivity and even mass mortality. Individual chicken physiological, physical, and behavioral symptoms—such as fever-induced body temperature increases, abnormal vocalization from respiratory disorders, and abnormal behavior from pathogenic infections—often reflect the animal's overall health. Birds who experience respiratory issues will make odd noises, such as snoring and coughing. The goal of the effort is to gather a dataset of both healthy and ill hens. Individual chicken physiological, physical, and behavioral symptoms—such as fever-induced body temperature increases, abnormal vocalization from respiratory disorders, and abnormal behavior from pathogenic infections—often reflect the animal's overall health. Birds who experience respiratory issues will make odd noises, such as snoring and coughing. The poultry research farm at Bowen University served as the experimental site. One- hundred-day-old poultry birds were purchased and divided into two groups. The first group was treated for respiratory ailments while the second group was not. The birds were then divided up and kept in cages under observation. The microphones were positioned a fair distance away from the birds in order to block out background noise and other sounds that might have an impact on the study. A 96 kHz sampling rate with 24 bits was used to collect the data. Three times a day— morning, afternoon, and night—audio data were continuously gathered for 65 days. Throughout this time, the birds are continuously supplied with food and water. The untreated group began to sound unwell with respiratory problems after 30 days. It was also mentioned that this information was unhealthy. The audio signals from the chickens were captured, stored in MA4, and then converted to WAV format for analysis.

Fuentes e al. (2020) discussed problems faced by farm animals as experiencing more heat stress due to rising global temperatures and climatic oddities like heatwaves brought on by climate change. These changes might negatively affect dairy cow productivity and milk quality. Four years' worth of data from a robotic dairy farm 36 cows with comparable heat tolerance and all 312 cows on the farm were used in this study. In order to create supervised machine learning fitting models that could forecast milk yield, fat and protein content, and the actual amount of concentrate feed consumed by cows, this data included weight and programmed concentrate feed paired with meteorological factors. The technical benefits of the proposed system are as follows; most dairy farms have access to readily available environmental data, and government services with nearby automated meteorological stations can also be used to base ML modeling, environmental data can be automatically extracted from government services by connecting an automated meteorological station to the RFID & ML Processing Unit directly and the digital database per cow can be implemented as part of the system to incorporate data like programmed concentrate feed, lactation days and number, frequency of milking, and liveweight. The staff of the dairy farm will need to update this cow information, and cows can be detected by the system using standard RFID technologies to collect cow data automatically from databases.

Atkins et al. (2018) study observed the dynamics of continuous breathing rate in nursing dairy cows. The developed sensor and signal processing algorithms were evaluated by contrasting their results with measurements obtained by visual observation of the rate of breathing. The findings indicate a consistent correlation between body temperature, respiration rate, and THI. At roughly 70 THI, the slopes of the correlations between body temperature and THI and respiration rate rise. It was found that when people lay down, their body temperature rose along with their breathing rate. Furthermore, even with a decrease in THI, body temperature and respiration rate continued to rise into the evening. This implies that even after the air temperature drops below the cooling system's ambient setpoint, cows might benefit if the cooling system is kept running later into the evening.

Ji et al. (2020) applied Robotic milking systems (RMS) in cows and discussed the underutilization of this system in livestock farming, despite evidence that they can decrease the amount of labor needed on farms and gather substantial individual-level data regarding animal health, welfare, and productivity. There are still not enough studies on the connection between animal behavior, heat stress, and robotic milking efficiency in an RMS. This study concentrated on examining the information gathered by an RMS system in order to model such a relationship. Rumination time (RT), milk temperature (MT), and daily milk output were the animal response indicators used in the heat stress assessment (DMY). Furthermore, the RMS milking behavior was observed, which includes the time of milking (TM), frequency of milking (MF), length of milking (MD), speed of milking (MS), and milk yield per milking (MY). The behavior of animals under heat stress and the functionality of robotic milking devices were the main subjects of this study. A 1°C increase in the daily mean temperature, when surpassing the thresholds, lowered rumination time by 5.12 min d^{-1}, decreased rumination efficiency by 0.07 kg.cow^{-1} h^{-1}, and increased the presence of low-efficiency milking by over 0.5%, per the regression analysis. Furthermore, in order to optimize the benefits of milk production and robotic milking performance, it was suggested that the first milking be postponed and the minimum milking interval be lowered to 4 hours for the RMS herd traffic control in this study.

Paudyal et al. (2016) examined the impact of the calving season, which is linked to varying degrees of heat stress, on the dynamics of rumination in the prepartum and early lactation periods in cows that were either healthy or had peripartum health issues. At the University of Florida Dairy Unit, 210 multiparous Holstein cows were fitted with a neck collar carrying rumination recorders, which recorded rumination time (RT) at 2-hour intervals, three weeks prior to the anticipated due date. In both the hot and cool seasons, ruminating on the day of calving was consistently decreased in both healthy and sick cows. In cows affected by severe negative energy balance and subclinical ketosis, the average daily RT prepartum and postpartum was shorter in only hot-season calvings. Cows with dystocia during the hot season had shorter daily RT prepartum; for calvings during the cool season, their RT postpartum was lower. According to the study, the variations between RT between healthy and sick cows are being affected by sickness, calving time, and the season. Specific medical problems and metabolic states influenced how heat stress affected sick cows' rumination patterns around calving. Cows with subclinical ketosis during early lactation and negative energy balance during the summer had considerably lower RT both pre- and postpartum than cows without these problems, but not during the winter.

2.3 AI System for Livestock Health Diagnosis

Atkinson et al (2020) highlighted that one of the main things that affects a cow's productivity and overall well-being is how healthy its digestive system is. In the dairy and beef industries, under- and overfeeding are both prevalent and can have detrimental effects on the environment, human wellbeing, and financial results. Unfortunately, there are a number of reasons why it is challenging for farmers to regularly check digestive health on big farms, not the least of which is the requirement to transport poo samples to a laboratory for compositional analysis. This research offers a unique approach based on computer vision to monitor the health of the digestive system

using an inexpensive, user-friendly imaging device. The technique entails quickly taking several pictures of feces in both visible and near-infrared light. Using a deep learning technique, the algorithm can also identify the presence of maize kernels and undigested fibers. In image regions, corn and fiber detection percentages were in the range of 90%. These findings suggest that this method could be used for real-time, on-farm monitoring of each animal's digestive health, enabling early intervention to successfully modify feeding strategy.
Alameer et al (2020) study, pig behavior changes can help identify early indicators of poor health and welfare. Due to harsh farming conditions, such as pigs blocking each other's path, automatic detection of pig behaviors by optical imaging is still difficult in commercial settings. In the study, two deep learning-based detection techniques were created to recognize the drinking habits and pig postures of pigs living in groups. During routine management, we first assessed the system's capacity to identify changes in these measures at the group level. Next, the study showed that our automated techniques could, under a range of conditions, identify the behaviors of individual animals with a mean average precision of 0.98.

Alameer et al (2020) leveraged on automated technology in animal husbandry to identify early behavioral changes that result from concessions to welfare and health. It is hard to manually quantify such changes; early automation-based identification, however, enables prompt intervention to stop further declines in animal welfare and related financial losses. This study offered a fresh approach to the current issues with automating the identification of pig behaviors connected to feeding. We have created a system to automatically track and report on the feeding and NNV behavior of group-housed pigs in commercial settings using video surveillance. We presented a unique automated approach that uses simply visual surveillance to detect these minor feeding behavioral changes with over 99.4% accuracy.

Alameer et al (2022) applied automated technology in pig farming sector to explore the possibility of identifying behavioral shifts in the pigs before they become unhealthy or unwell. Manual measurement of these alterations is unfeasible; early automation-based detection should allow prompt action to minimize animal welfare violations and related financial losses. In order to assess interactions (head-to-rear contact) between pigs kept in groups, a novel solution was put forth in this research. The technique relied on image processing and machine learning, which are well-known. Deep learning networks have been created to identify and classify components of pigs. The study created a small processing module that calculates intersection scores between pigs quickly. Because it was employed in a variety of scenarios, the study presented a workable implementation for detecting interactions between many pigs using video surveillance (infrared and RGB).

Kyriazakis et al (2023) implemented an automated technique that records alterations in behavior linked to the post-weaning shift in pigs. The approach is data-driven since it uses carefully annotated data from a behavioral scientist to accurately identify the changes within each relevant behaviour. It is based only on video data that has been acquired, without the need for extra pig markings or sensors. During the first week after weaning, when there is a high risk of post-weaning diarrhea, the approach measured the group's overall feeding and drinking behavior as well as posture (i.e., standing and non-standing). The technique was used with and without in-feed antibiotics, which are anticipated to have an immediate impact on piglet health and performance by reducing the likelihood of gastrointestinal diseases after weaning. The automatically measured alterations in behavior matched the consequences of the antibiotic shortage on pig health and performance, which showed up as looser feces and decreased feed efficiency. Antimicrobial therapy was observed to be insignificant to pig feeding behavior, which continued to rise with time. The system developed here has the potential to be valuable as a diagnostic tool because it can automatically monitor multiple behaviors of a group of pigs at the same time.

According to Cuan et al. (2022), Newcastle disease (ND) is a prevalent ailment that significantly affects the well-being and yield of poultry. ND damages the respiratory system, changing the characteristics of bird vocalizations' sound. Because of this, a novel technique for the early identification of ND based on chicken vocalization was developed by the authors: the deep poultry vocalization network (DPVN). To lessen the impact of noise, the technique combines high-pass filtering and multiwindow spectral subtraction. This research suggested a multiple sub band poultry vocalization endpoint identification approach for automatic detection of chicken vocalizations. The intersection-over-union (IOU) between the detected and ground truth vocalizations was used to assess the detection method's performance. The detection method's precision was 96.54%, and its recall was 95.11%. In order to identify the vocalizations of poultry afflicted with Newcastle disease, sound technology extracts the audio features from the vocalizations of the birds and uses them as input for a deep learning network. In the experiments, five distinct models were contrasted. The approach employed in this work yields the best results, with accuracy, recall, and F1-score of 98.50%, 96.60%, and 97.33%, respectively, being the highest. In the first, second, third, and fourth days following infection, the accuracy rates were 82.15%, 90.00%, 93.60%, and 98.50%, in that order. The figure below showed an animal with a sensor on, such that (a) represent a wearable device for collection of physiological features of animals such as heart rate or respiration rate, (b) smart ear tags to track and monitor movement of animals, and (c) smart nose tag to measure milk yield or body movement such as resting, lying down or other activity.

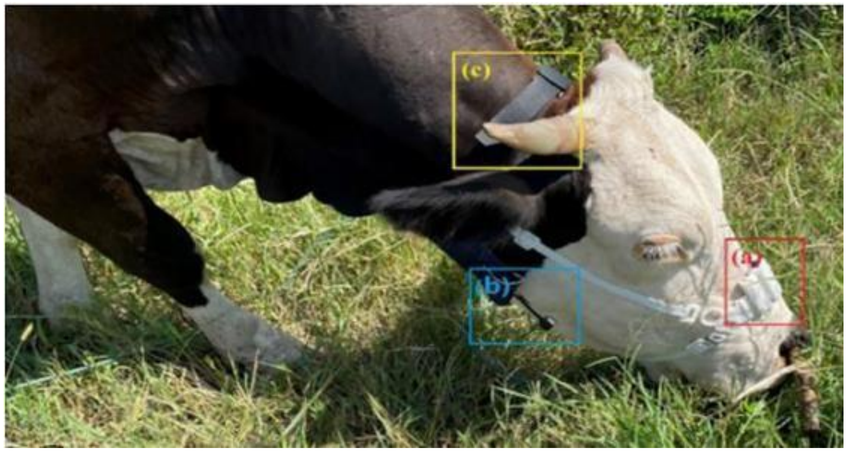

Figure 1: Modeling animal feeding behaviour

Source: Chen et al., 2022

Fehlmann et al. (2017) discussed three modes of motion are lying, standing, and walking. Individual animal behavior cannot likely be manually detected. Therefore, several machine vision-based algorithms and sensor-based systems were integrated with Bluetooth, Wi-Fi networks, and radio frequency technologies in order to identify the environmental conditions and activity of the animals. Animals' necks, ears, jaws, and legs are fitted with inertial devices equipped with uniaxial or 3-dimensional accelerometers to collect activity data. The figure below showed the area of data collection of an animal overall activity.

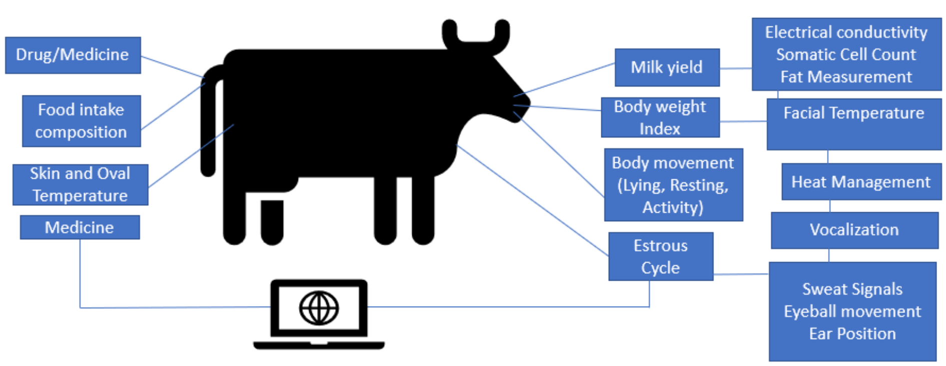

Figure 2: Data collection and analysis on animal

3.1 Methodology

The methods proposed in this study for the application of farmer centered artificial intelligent systems in livestock farming in order to optimize operation and provision of improved welfare. It is critical to collect dataset big enough for training the artificial intelligent systems so it can capture all features or physiological, environmental and behavioral of animals, Table 1 describe the animal features that can be capture, the description of AI applications, and potential benefits for farmers. While Table 2 present the AI technologies, algorithms, the type of collected data needed to train or develop the AI system, and the purpose of having such system.

Table 1: Overview of Animal Features, Observation Methods, AI Applications, and Farmer Benefits in Precision Livestock Farming

Animal features	**Effect on livestock**	**Description**	**Farmer centered advantage**	**Reference**

Behavioural	Instant or early observation of illness or stress in livestock.	The use of AI systems to analyze sensor data to detect animal behaviour.	The farmers are quickly notified about the wellbeing of livestock, this can then save livestock from spreading an infection or potential death.	Giovaneti et al., 2017
	Aggressive behaviors in pigs	The use of Artificial Neural Network in detection of pig aggressive behaviors.		Oczak et al., 2014
Physiologica l	The AI systems sheds light on the inclinations and actions of animals.	The use of AI systems would Improve the relationship between farmers and their livestock.	It helps to enhances the emotional connection and makes farming more enjoyable.	Fuentes et al., 2020
	Measurement of the environmental impact on dairy cow behaviors.	The use of machine learning algorithms in measuring environmental effect on animals' behavior.		Wagner et al., 2020

Environmental	The AI systems helps to modify the environment with sensors to track and monitor environmental variables.	It would provide optimal living conditions for livestock within the environment.	It helps the farmers to ensures that animals are treated ethically by giving them comfort.	Gorczyca, and Gebremedhin, 2020.
Health Diagnosis	The monitoring of vital health signs with AI systems. The observation and detection of disease and abnormal behaviour in livestock	It provides a proactive health management. Early detection of disease and abnormality in livestock.	It helps to reduce casualty among livestock due to health issues. Detection of Newcastle disease.	Jorquera-Chavez et al., 2020. Cuan et al., 2020.
early disease in animals.	Animal feeding habit.	Feeding habit early detection for quick intervention in animals.		Atkinson et al., 2020.

Table 2: AI techniques on livestock data

AI Techniques	Algorithms	Data collection	Purpose	References
Natural Language Processing	Gradient Boosting, Bag of Words (BoW)	Semantic cell	Detection of semantic cell contact and electrical conducting for animals suffering from mastitis.	Ebrahimi et al., 2019
Computer Vision	Optical flow, You Only Look Once (YOLO), Vision Transformer (ViT)-22B	Animal movement (Behaviour).	Detection of mobility, direction and speed changes in animals suffering from swine flu disease, detection of body and leg movement in video data capture.	Zhang et al., 2019
Classification	support vector machines, random forest, Logistic Regression	Protein measurement	Detection of protein production, milk and lactose production.	Hidalgo et al., 2018

Time series and linear regression	Autoregressive Integrated Moving Average (ARIMA), linear regression	Daily feed consumption	Detection and measurement of consumed foods.	da Rosa Righi et al., 2020

The use of these AI technologies with the listed algorithms in modeling the behavior, physiological, environmental and health tracking of these animals would help farmers improve livestock operation, hence improve the health of these animals. However, the development of these AI technologies into useable device could be expensive for individual livestock farmers, hence the need for government involvement for partnership and regulation to avoid misuse.

The AI devices or tools used in enhancement of precision livestock farming, the purpose it fulfills and where it is located is discussed in the table below.

Table 3: AI Devices for Livestock

AI Devices/Tools	Purpose	Collected Data	Challenges	On or Off Farm	References
Livestock Monitoring Drones	Drones with cameras and other sensors allow for airborne monitoring of pastures and cattle, giving managers of the land and herd health a more comprehensive view.	Environmental	Animal movement	On-arm	Al-Thani et al. (2020)
Smart Ear Tags	These are gadgets with sensors built in to track an animal's whereabouts, activity level, and health metrics.	Animal Behaviour	Milk yield measurement	On-farm	Girish and Barbuddhe (2020)
Wearable sensors	Wearable technology that monitors physiological parameters including heart rate, respiration rate, and body temperature might shed light on cattle health.	Animal Physiology	Heart and respiratory problems	On-farm	Neethirajan (2017)

Precision livestock farming Apps	Applications for smartphones that let farmers control and keep an eye on many facets of raising livestock, such as reproduction, feeding, and health, from a distance.	Animal Health	Feed and reproduction monitoring	Off-farm	Aquilani et al. (2022)
Livestock Tracking system	RFID tags or GPS-enabled devices that track livestock's position in real time, assisting in management and reducing loss.	Animal Behaviour	Loss management	On-farm	Molapo et al. (2019)
Smart Watering system	AI-driven systems that keep an eye on and control the water supply for cattle to make sure they are properly hydrated.	Environmental	Water management	On-farm	Hsu et al. (2021)
Livestock Health Apps	Farmers can get information about livestock health and management, monitor health metrics, and receive alerts through mobile applications.	Animal Health	Health and farm management	Off-farm	Michels et al. (2019)

3.2 Discussion

This study reviews the position of farmers and Artificial Intelligent systems in livestock operations, considering that animals also fall sick, depict some form of psychological and behavioral attitude. Hence, the use of Artificial Intelligence models integrated in sensors or technological devices but the result obtain with the application of this Artificial Intelligent driven systems is not optimal in livestock operations, and when livestock farmers are not involved who then will be responsible for measuring the effectiveness of the AI technologies on livestock? In view of this, animal farmer is proposed to be included in application of AI driven systems in livestock operation to achieve an effective and optimal operation. Also, the study reviews different AI algorithms and how they can be used to measure the health, psychological and behavioral attitude of animals, with the use of natural language processing techniques to process and model animal sound to evaluate their health, behavior or psychology. Computer vision techniques was used to model animal behaviour, health or psychology through sound, machine learning technique such as regression or classification was used in protein measurement in relation to their health, behaviour, and psychology, while time series techniques was used to model feed consumption over a period of time, the trend could also help to measure the health, behaviour, and psychology in animals as feeding well could be attributed to healthy well being (Malhotra et al, 2023).

The information presented in both tables above showed the benefit of having a farmer centered AI systems such that the livestock behavior, physiology, health and environment could be monitored with the use of AI systems, however the farmers are experience and could help AI expert point to the right data that would be used to train the AI technologies, where necessary data such as images, voice, and motion, feeding habit among others could be used to train algorithms such as natural language processing, computer vision, time series, classification and regression problems. The expected result from the application of these AI-farmer centered systems in livestock farming would help in quick detection of disease as such infected animals could be isolated for treatment and help avoid the spread of the disease to other animals. Also, the movement, sound and feeding of animal monitoring could provide insight into the healthiness of these animals, and it is interesting to know that cow devices could be used for pig and other mammals only with the modification of body images, movement video, and voice (Neethirajan, 2023). This would as well help farmers save resources in terms of manpower, farming materials and staff as much of the work would be carried out with the use of AI systems. However, it is important to note that regardless of the innovation of these systems there is a need for privacy hence the need to be evaluated and given the necessary pass (Neethirajan, 2023).

4.1 Conclusions

Conclusively, application of Artificial Intelligent-Farmer Centered systems in livestock farming as reviewed in this study showed these technologies are in used although not as wide as it could have been thought. However, the wide adoption of AI-Farmer centered systems would help reduce cost of operation by ensuring only staff that would interpret the technical result from the systems are employed staff as such increase profit making.

4.2 Significance of the study

The study is significant as it contributes to existing literature on tremendous benefits that await livestock farmers on full adoption of AI integration in livestock management, as it would optimize mode of operation and reduce loss.

4.3 Future directions

Future study should consider the adoption barrier such as cost and lack of awareness among other reasons. Also, understudy or deepen the study on farmers trust of AI systems, and spot potential problems likely to be faced.

Conflict Of Interest Statement

The authors have no conflicts of interest to declare.

Funding Statement

It is an independent research that provides insight into integration of AI in livestock management.

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