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Applications and Future Perspectives of Artificial Intelligence in Animal Health

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Summary: The advent of AI in the animal health sector, with specific emphasis on automation, sensors, blockchain traceability, and farm management indicate significant revolutions in livestock farming. Artificial intelligence (AI) has the potential to significantly improve animal health and management techniques in the future. AI has the potential to greatly improve diagnoses and treatment methods in the field of animal health. Machine learning algorithms can find trends and forecast diseases before they appear clinically by analyzing massive volumes of data from multiple sources, such as genetic information, environmental variables, and past health records. Modern technology facilitates remote health checks, helps farmers increase productivity and improves the level of transparency. Future AI breakthroughs might lead to more advanced prediction models and environmentally friendly farming techniques, assuring the efficacy and long-term profitability of animal husbandry.
Keywords: Livestock farming, Artificial intelligence, Animal husbandry

INTRODUCTION

Artificial Intelligence (AI) refers to a system's ability to perceive and learn from external inputs, adapting to fulfill certain goals and activities. AI corresponds to mechanical intelligence, which differs from natural intelligence seen in people and animals. Computers replicate human cognitive functions, such as learning and problem-solving. Over the decades since 1959, artificial intelligence has experimented with numerous strategies. It involves stimulating the brain, simulating human behavior, reasoning, and problem-solving techniques, as well as databases of information. However, there has been little to no practical use of AI, even after it was established as an academic field. The phrase "artificial intelligence" was first introduced by John McCarthy.The inventors of artificial intelligence were Herbert Simon, Arthur Samuel, Marvin Minsky, Allen Newell, and John McCarthy. Their students created programs that were praised for their incredible computing skills (Russell & Norvig, 2003). Those programs supposedly proved to be more skilled than the typical person and could solve algebraic word problems and produce logical theorems. One of the AI pioneers, Herbert Simon, was optimistic, arguing that "in the next twenty years, machines will be able to compete with a man in any field." (Haenlein & Kaplan, 2019).

AI is interdisciplinary and encompasses data science, software engineering, mechanistic modeling, and statistics. The interfaces that AI has developed with other sectors, including biomedicine, and the vast amounts of data from other domains, especially healthcare, have boosted recent advancements. Emerging technologies are being deployed across all economic sectors, including the agriculture and livestock sectors (Ezanno et al., 2021). The idea behind "smart agriculture" is that commodity producers may automate as many agricultural processes as possible, boosting yields and improving financial metrics, by utilizing a variety of creative methods. The launching of IoT platforms serves as its foundation. It is a unique type of software created to provide remote access to the "Internet of Things" (sensors, controllers, and other devices) via cloud connectivity. Smart agriculture technologies include precision livestock farming (PLF), unmanned aerial vehicles and drones, and artificial intelligence-operated applications like big data and machine learning. PLF is a comprehensive strategy that uses information and communication technologies (ICT) to advance farming activities. Precision livestock farming employs ICT to boost animal health and productivity while lowering investment expenses. The principal aims of PLF are as follows: (i) determine the optimal livestock feeding practices; (ii) mitigate environmental effects by optimizing resource management; (iii) align crop processes to assure optimal livestock feeding; (iv) guarantee food safety by means of product traceability and (v) enhance animal well-being and productivity (Garcia et al., 2020).

These targets will be advanced by the processes of digitalization. Farmers and animal scientists may therefore use the technological services of PLF in order to progress in digitizing livestock agriculture to cope with the increase in demand for animal protein that is related to environmental sustainability, public health, and animal welfare. The influence of PLF technology on animal health, animal husbandry practices and food safety and traceability is highlighted in this chapter.

DOMAINS OF ARTIFICIAL INTELLIGENCE

Artificial intelligence encompasses techniques including machine learning, deep learning, computer vision, natural language processing, and robotics that are very impactful in several fields, including animal farming.

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Machine Learning

The technique of using mathematical models of data to teach a computer to learn without explicit instruction is known as machine learning, or ML. By using algorithms, it is possible to find patterns in the data and build a model that will be used to make judgments and predictions in the future (Kotsiantis et al., 2007).

Data collection: The very first thing to do at the beginning of any machine learning project is to acquire appropriate data. Data could be structured (e.g., databases) or unstructured (e.g., text, images, audio).
Data preprocessing: Machine learning models usually need to be trained on preprocessed raw data. This first step involves operations such as data cleaning, values imputation, standardizing or normalizing the data, and format conversion.
Feature extraction and selection: In many cases, not all the raw data gathered is useful in training the model. It refers to the process of selecting the most important features and rejecting the ones that are either irrelevant or redundant.
Model selection: There are various types of machine learning models, each fit for particular problems and data. Common types of models include: supervised learning, unsupervised learning and reinforcement learning. Algorithms using supervised learning rely their predictions on a collection of labeled samples from prior experience. It is used when the outcome is known. Unsupervised learning entails the model learning from the unlabeled data. The model targets the identification of patterns or structure in the data without explicit instructions. It's beneficial when no information about the outcome is known. In Reinforcement learning algorithms, that determine the best course of action is determined based on results. Feedback is given to the algorithm to assist it in deciding if the decisions it made were right, wrong, or undecided. In this instance, some of the data is tagged and some is not. This type of learning closely resembles how humans acquire skills and the majority of natural processes (Kour et al., 2022).
Training the model: After the model is selected, training follows on the preprocessed data. The model undergoes parameter update during training, which is based on the training data and the target output. The goal is to reduce the distance between the model's outputs and the ground truth values.
Evaluation and validation: The model trained is then evaluated on the validation or test set. This lets us test the model on unseen data and diagnose various problems, including overfitting (when a model performs well on training data but poorly on new data) or underfitting (when a model is too simple to recognize underlying patterns in the data set).
Model deployment: After the model has been trained and evaluated to satisfaction, it can be deployed to make predictions on unseen data in real applications. Deployment entails connecting the model to the existing systems, system platforms for optimization, and monitoring its performance over time.

Deep Learning

The area of machine learning known as "deep learning" focuses on techniques that are based on the design and functionality of neural networks found in the human brain. Deep learning is based on artificial neural networks (ANNs), including convolutional neural networks (CNNs) and deep neural networks (DNNs). These are computer models based on the structure and function of human neuroanatomy. ANNs are made up of interrelated nodes that are organized into layers. Each node is also a neuron that executes a simple operation, and the information flows through the network by using the connections that are weighted. It takes in raw data and improves the graphical representation of that data. (Kour et al., 2022). Deep learning is frequently utilized in applications such as computer vision and natural language processing (NLP). Deep learning has changed the way computer vision and NLP tasks are done through deep neural networks, e.g., image classification, facial recognition and image segmentation, object detection, language translation, and sentiment analysis (Mijwil et al., 2023).

AI APPLICATION IN ANIMAL HEALTH

In the past ten years, significant advancements have been made in manure management, automated feeding systems, milking robots, and instrumentation, as well as in maximizing production efficiency through nutrition and animal breeding and genetics. Despite these developments, challenges remain. The growing demand for animal products necessitates intensive livestock management, but farmers find it challenging to keep a close eye on animal health due to confined livestock housing. Traditionally, farmers would care for fewer cattle and have direct contact with them. However, on modern computerized farms, few humans handle a greater number of cattle, and there is less direct interaction. As a result, it becomes more important to keep an eye on the animal's health (Helwatkar et al., 2020). Moreover, the likelihood of illness, heat stress, and other health problems for livestock animals will rise in combination with the acceleration of climate change. 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 financial losses. Many different kinds of technologies have been used for efficient health monitoring. There are several methods in prediction and diagnosis of the disease and it includes selection of the AI model and the training of the model. During training, the AI model learns the features and associations of the outcome of the disease. AI can detect carcinoma cells in the body. Moreover, several instruments that are attached to the animal body detect animal activity. Any change in the activity or deviation from the normal behavior indicate the problem in the animal (Ali, 2023).

Biosensors and Underlying Technologies

A sensor is a device that monitors biological or behavioral characteristics of an animal. It makes it possible to automatically identify changes connected to health occurrences on farms and necessitate the farmer to take action.

Table 1. Sensors used for the assessment of body temperature, variability in heart rate, respiration rate and sweating rate

Types of Sensors	Purpose of Sensors	References
Thermal Infrared (TIR) Sensors	Used for the assessment of body temperature	Stewart et al. 2010
Textile-based wearable sensors (Hexoskin or Biometric Shirt)	Used in the measurement of respiration rate, variability of heart rate and maximal consumption of oxygen	Neethirajan, 2020
Respiratory Sensors	Used for accurate monitoring of respiration rate	Strutzke et al. 2019
Immuno-Sensors	Useful in the assessment of biological fluids (sweat and saliva) and Hormones (lactate and cortisol)	Neethirajan, 2020

In order to manage animal health, wearable technology and biosensors are becoming more and more crucial. These tools can diagnose animal illnesses quickly and accurately if they are made with precision and used appropriately, which will ultimately reduce financial losses. Animals can be implanted with sensors and wearable technology to monitor body temperature (Sellier et al., 2014), identify stress, study behavior and movement (Van Nuffel et al., 2015), monitor sweat constituents (Heikenfeld, 2016), analyze sound, detect ruminal pH changes, prevent illness, and identify the presence of viruses and pathogens. The livestock industry is undergoing a paradigm shift in disease identification to address challenges in surveillance, diagnostics, and control of diseases in farmed animals. This shift aims to improve biosecurity and animal traceability. Therefore, in order to facilitate quick, real-time, on-farm disease monitoring and record keeping, the livestock industry is searching for new tools and technologies.

Biosensors

Biometric sensor technologies provide accurate, unbiased measurements of animal health. There are 2 constituents of biosensors: a transducing device and a recognition element. The recognition element operates on affinity-pairing mechanisms, for example, enzyme-substrate and antibody-antigen receptors. In response to biological activity, the transducer generates detectable electrical signals that are subsequently analyzed by algorithms (Mungroo & Neethirajan, 2014). For example, thermal infrared (TIR) imaging can be used to track body temperature instead of invasive thermometers that need handling and restraint of the animals. This technique uses infrared thermal imaging cameras that act as a thermometer and provide a measurement of temperature in a 2D image called a thermogram. In comparison to conventional methods, TIR of the eye region and general skin temperature can monitor stress and detect disease 4-6 days earlier, allowing for prompt treatment and limiting the potential for illness to spread throughout flocks or herds (Martinez et al., 2020). Heart rate monitors can also be used to track metabolic energy production and general health. Blood volume variations in the tissue's microvascular bed are detected by Photoplethysmography (PPG), an easy-to-use, non-invasive optical measurement method. To continuously monitor the heart rates of livestock, photoplethysmography sensors are easily attached to ear tags or other body parts (Nie et al. 2020). Sensors used for the assessment of body temperature, variability in heart rate, respiration rate and sweating rate are summarized in Table 1.

Detection of subclinical ketosis

Ketosis is characterized by an elevated level of Beta-hydroxybutyrate. Early detection of subclinical ketosis can be done by Quantum-Dots integrated Microfluidic technology. This technology depends upon the conversion of nicotinamide adenine dinucleotide (NAD+) to its reduced form, β-nicotinamide adenine dinucleotide (NADH), by the enzymatic catalysis of βHBA to acetoacetate. Here, fluorescent nanoparticles known as quantum dots (QDs) are pre-conjugated with NAD+. The variation in βHBA concentration in samples can be deduced from the shift in fluorescence intensity exhibited by cofactor-conjugated QDs. This biosensor can measure βHBA quickly and accurately by coupling it further with a microfluidic platform and optical detection unit. This Biosensor is highly sensitive and specific towards β-HBA, with a detection limit of 0.05 mM (Weng et al., 2015).

Detection of an infectious agent

The increasing challenges of infectious diseases in intensive livestock farming highlight the need for innovative and efficient disease detection methods. Rapid and accurate screening for livestock diseases can be made possible by an integrated system that combines microfluidic blood testing on-farm with multivariate sensor data analytics (Gunawardena & Silva 2022). One such example is the recognition of Bovine Herpes Virus-1, which is the causative agent of Bovine Respiratory Disease. The Field Effective Sensor can directly perform serological analysis and provide a platform for rapid immunological testing (Tarasov et al., 2016). The use of biosensors for the diagnosis of different diseases in animals is summarized in Table 2.

DISEASE EARLY WARNING SYSTEMS/EPIDEMIC INTELLIGENCE

AI has the potential to be a game-changer in the generation of automated early warning systems for epidemics by utilizing massive amounts of publicly available data with little to no human involvement. To apply AI to outbreak detection, it is necessary to: 1) process a large amount of multidimensional open-source data through natural language processing (NLP) to identify early warning signals; 2) highlight regional and local trends in the signals that are detected; 3) model and simulate outbreak behaviours; and 4) quickly identify false information that could compromise pandemic preparedness. There are currently a number of digital systems available for identifying significant public health events early on. The scope of the systems varies according to the kind of event they cover. Events can be classified as either exclusively human diseases, diseases affecting humans and animals both, or exclusively animal or plant diseases, or infectious diseases. They can also include non-communicable diseases, natural disasters, and humanitarian crises. When it comes to infectious diseases, a One Health approach works best. In accordance with this approach, an end-user should have access to a variety of services, including risk analysis tools, geographical heat maps,

Table 2. The use of biosensors for the diagnosis of different diseases in animals

Name of Disease	Purpose of Sensor	Type of Sensors Used	References
Bovine Viral Diarrhea (BVD)	Detection of BVD Virus in serum	Nanowire-based Immunosensor	Luo et al., 2010; Montrose et al., 2015
	Detection of antibodies against BVD Virus	Electrospun biosensor	
Foot-and-Mouth Disease (FMD)	Rapid diagnosis of FMD Virus	SpectroSensTM optical microchip sensors	Bhatta et al., 2012
Bovine Respiratory Disease	Serologically viral protein diagnosis of Bovine Herpes Virus (BHV-1)	IgE-coated immunosensor	Tarasov et al., 2016
Avian Influenza (AI)	Detection of AI virus strains: 2 strains of H7 & 1 strain of H8	Interferometric biosensor	Xu et al., 2007; Bai et al., 2012
	Detection of H7N1	Miniaturised gold electrode biosensor	
	Quick detection of H5N1 in swab samples	Surface Plasmon Resonance (SPR) -based biosensors	
Porcine Reproductive and Respiratory Syndrome	Detection of PRRS Virus	Immunodetection-based biosensors	Neethirajan et al., 2017
Subclinical Ketosis	Real-time detection of beta-hydroxy butyrate from the milk or blood	Nanobiosensors	Neethirajan et al., 2017

news reports, and mobile applications, whether they are public health officials from a national agency or an ordinary citizen (MacIntyre et al., 2023).

The Program for Monitoring Emerging Diseases (ProMED-mail) is the most commonly used outbreak alert system. ProMED-mail has been monitoring emerging diseases in animals, plants, and humans since its inception, following the concept of one medicine. To provide expert risk assessment and qualitative reports of events of interest, this system primarily depends on a network of health professionals (Cowen et al., 2006).

National Surveillance System in Pakistan

The first weekly reporting-based surveillance system in Pakistan, known as the Electronic Disease Early Warning System (eDEWS), was established by the World Health Organization (WHO) in partnership with the Ministry of Health and the National Institute of Health. The eDEWS is effective in alert detection and early outbreak containment. eDEWS aims to capture data using mobile software, securely transmit and analyze it, generate alerts, and share information with key stakeholders. Additionally, it will make it easier to identify national public health threats and to report diseases more accurately, quickly, and timely. The data transfer will be facilitated with GPRS and web-based reporting when possible; data will be managed in a more effective way so that the utility of the obtained information will be maximized with an online software application. The alerting system will be enhanced by embedding an automatic alert-detecting algorithm in the software, which will trigger an alert as soon as a threshold is crossed and will communicate with the target group (DEWS Response team) with 24 hours alert notification.

AI APPLICATIONS IN ANIMAL HUSBANDRY

Commonly Used Automation in the Dairy Industry

The challenges faced by the dairy farm owners in finding workers willing to conduct manual labor on their dairy farms have been overcome via automation with the help of data collection, lasers and sensors (Table 3). The means of automation are used in the operation of farms to increase the quality and production of meat and milk products, with the reduction in the cost and expenses of farming (Patel et al., 2022). One advantage of automation is that animals seem to have acclimated to the new trend of AI technology and have a preference for robots (Ezanno et al., 2021).

APPLICATION OF AUTOMATION AND SENSORS AT THE FARM LEVEL

Artificial intelligence can simplify livestock production in a number of ways. Computer vision and predictive analytics are employed in a large number of them. Detection of mastitis, FCR improvement, to increase the quality of feed, Evaluation of pasture, Animal welfare monitoring, monitoring drinking and eating habits, robotic vaccine delivery system are the applications of AI at the farm level (Melak et al., 2024). Other applications are given below:

Animal Identification

Tracking of animal involves uniquely identifying each animal using an electronic identifier for the duration of the animal's life. Worldwide recognition is growing for Radio Frequency Identification (RFID) as an animal identification technology, and it's become a major aspect of livestock management in various countries. The RFID is read by the electronic ear tag, which then stores the information in its processing unit. A satellite receives the data and sends it to a hub server, which receives the information about each animal. Tram identification is another method of identification that is used in many countries (Ali et al., 2020).

Water and Manure Management

The management of water and manure is crucial since the health of animals is closely linked to water, and the health of the community is compromised by animal dung. In an effort to address the problem of water scarcity, numerous methods have been developed for recycling the water from animal use. The amount of animal faeces produced is likewise dramatically rising with the number of animals. It has always been difficult for farmers to deal with animal manure because

Table 3. Different types of automations used in the dairy industry

Type of Automation	Benefits of Automation	References
Use of Robots	1. Reduction in labor cost (robotic milking machines and udder cleaning) 2. Improve biosecurity measures (cleaning & sanitization of barn reduces risk of contamination & disease transmission) 3. Enhance the productivity of animals (monitoring animal health)	Patel et al., 2022; Melak et al., 2024
Use of Internet of Things (IoT)	1. Monitoring feed intake and the health of animals 2. Communication among different systems and devices for sharing information & data collection 3. Enables automated milking operation and helps in dairy products marketing 4. Allow integration of tracking devices & sensors (monitoring of optimal environment conditions) 5. Improve profitability, efficiency and productivity of dairy farms	De Vries et al., 2023
Use of Augmented Reality (AR)	1. Helps in accessing and monitoring cows. 2. Enables effective & efficient management of livestock farms 3. Enhance the accuracy in the estimation of milk production 4. Reduction in the labor costs associated with monitoring and assessment of animals 5. Identification of potential health problems 6. Reduction in the risk of human error (provides more accurate data)	Liu et al., 2020; Melak et al., 2024
Use of Drones	1. Monitoring the health of the animal 2. Improve management of the herd 3. Monitoring growth of pastures (mapping, examination and photography of pasture) 4. Tracking & identification of diseases	Melak et al., 2024; Fuentes et al., 2022
Use of Blockchain	1. Ensure the safety & traceability of food (fulfills safety standards & connects points of origin, production, and distribution) 2. A distributed database system that stores and shares product data securely (like nutritional profile & expiration dates) 3. Detection of counterfeiting & food fraud 4. Connection of every link from producer to consumer in the food supply chain 5. Provide access to detailed information on the production process and its impact on the environment.	Melak et al., 2024
Utilization of the 3D Printing	1. Production of complex machine parts to save money and valuable time 2. Useful in the reproduction of food like cheese 3. Improvement of the variety and quality of food available for the consumers 4. Help in the combination of different layers of food that is balanced nutritionally and visually interesting.	Ezanno et al., 2021

they lack the knowledge to store and dispose of it appropriately. Traditionally, some methods are used for the management of manure, which include urine containers, pads, and heap formation. The manure that is produced can either be solid or liquid, depending on whether it is mixed with water for irrigation or used for biogas and energy production. Moreover, thermochemical conversion methods can be used to transform animal faeces into oil products (Ali et al., 2020).

Automated Weighing System

A key component of maintaining quality control is weighing. What matters is that animals who attempt to avoid using the scale typically experience stress, so automation made it easier. Sensitive sensors do not require manual scanning as they can quickly and correctly detect weight and instantly enter the results into the database. An artificial intelligence system can process this data and extract insights that can be used to enhance farming methods (Melak et al., 2024).

Monitoring Heat Stress using Temperature Analysis

Farm animals are susceptible to heat and ultimately experience heat stress, which decreases their productivity (Neeteson et al., 2008). The AI-based system's sensors can collect temperature data, derive information about the rises and falls, and associate it with particular actions or behaviours. When the temperature hits an unsafe level, the machine learning model delivers a real-time notice because it detects patterns that raise the risk of heat exhaustion (Rosati, 2024).

Automated Milking

Automated milking is one of the widely used techniques to overcome the issue like labor cost and prolonged time. The sensor cups on the automated milking machines can be individually affixed to each cow's teat. The equipment may also automatically clean and sanitize the teats. Moreover, machines are able to identify the color, quality, and contaminants in milk. If the milk is not fit for human consumption, it is transferred to another container (DE Vries et al., 2023).

Animal Reproductive Performance:

An automated tool called radio-telemetry is used to identify an animal's estrus. Although expensive, it doesn't cost any more than the loss of missing an estrus cycle. Pedometers, which are attached to an animal's legs and compare past and present behavior, are another highly useful tool for identifying the estrus cycle in animals. A simple microphone chip can also be used to identify the voice of animals in heat. A developing method for assessing fetal-maternal circulation during pregnancy is called contrast-enhanced ultrasonography (CEUS). ELISA is one well-known modern technology that can be used to assess reproductive success in the animal production industry. Moreover, during the estrus

Table 4. Different types of AI applications in animal welfare

Type	Application	Reference
Animal health and nutrition	An intelligent learning model gathers the feed intake from cows in automatic feeding systems, then uses it to create a schedule of feeding. Intelligent learning systems are useful in monitoring the health of animals, monitoring the feed along with its safety, tracking of animals and milk quality and supply chain.	Zhang et al., 2023
Animal emotion and behavior recognition	The effective system of robots and sensors used for the management of the poultry house around-the-clock. Sensor utilization & machine learning frameworks are useful in the prediction of daily composition & milk production, along with the frequency of milking in dairy animals. Utilization of advanced processing of image and machine learning techniques helps to identify & analyze the emotional states of animals accurately.	Park, Britton et al. 2022; Ji et al., 2022; Zhang et al., 2023
Animal disease monitoring, prediction and diagnosis	AI has become a potent diagnostic tool for animal diseases through the use of extensive data analysis of clinical symptoms, medical imaging and laboratory test findings. The health of animals is monitored by automation with the help of an IoT-based "live care" framework on large dairy farms.	Zhang et al., 2023
Animal Living Environment	A proper system of monitoring the speed of wind, temperature and carbon dioxide in poultry. Intelligent robots with navigation guided by magnetic RFID technology are designed to target all aspects of disinfection protocol used in livestock farms.	Zhang et al., 2023

cycle, a specific set of hormones is released that affects the movement and behavior of the cow. For example, a cow in standing heat is more likely to remain still for an extended period of time so that other cows can mount her. By combining recently acquired movement data with previously stored data, the AI component may predict when the cow will ovulate (Ali et al., 2020).

The application of AI in the Improvement of Animal Welfare

The applications of AI in monitoring animal welfare are summarized in the table 4. Sensors used for the assessment of movement, activity, and postural behaviors are given below in Table 5.

Sensors Used for the Assessment of Water and Food Intake in Animals

Nose band sensors (Rumi watch): This sensor is useful in monitoring the ruminating and eating activities in dairy animals. Wearable sensors measure the actual physiological parameters on a large scale in a farm and enable quick reaction times with the immediate analysis of data from these sensors (Zehner et al., 2017; Neethirajan, 2020).

Wearable accelerometers: It is a useful tool in measuring the behavior of cows (Benaissa et al., 2019). HOBO accelerometers are fixed with the jaws of cows enables the recording of the time that animals spend ruminating and grazing (Rayas-Amor et al., 2017). Neck-mounted Accelerometers: They are used for the assessment of cow ingestive behaviors based on a decision-tree algorithm or a multi-class support vector machine (SVM). The neck-mounted triaxial accelerometers are also used to measure the drinking events (Vázquez Diosdado et al., 2015; Williams et al., 2020).
Radio-frequency identification tags (RFID tags): In RFID systems, an RFID antenna and transponder (ear tag) are placed at the feeding unit or drinking unit for tracking the drinking behaviour and feeding duration of each pig (Maselyne et al., 2015).
Sensors used for monitoring the movement of the jaw: Different types of sensors can be used to monitor the movement of the jaw (Table 6).

Other Types of Sensors used in the Livestock Farming

Bolus sensors: These wireless intraruminal sensors were developed to monitor the values of pH and temperature of the reticulum and rumen (Arai et al., 2019).
Rumen sensors: These wireless and indwelling sensors help in the continuous measurements of the high-resolution pH of the rumen, which identify the acidosis in the rumen and also assess the physiological status of the rumen (Dijkstra et al., 2020).
Surface plasmon resonance imaging(SPRi) biosensors: This optimized biosensor is used for the detection of molecules of progesterone ultra-sensitively (Zeidan et al., 2016).
Non-dispersive infra-red (NDIR) -based sensors: These sensors are used as a multi-point system for monitoring the levels of carbon dioxide in naturally ventilated barns of dairy cattle. The area and length of the barn help in calculating the number of NDIR sensors needed to accurately depict the total carbon dioxide concentration of the dairy cattle barn (Mendes et al., 2015).

Herd navigation system: This system is the integration of five sensing systems includes the level of progesterone in milk and suggests the times of insemination, early termination, animals for final confirmation of pregnancy, prolonged anestrus and cows at risk for cysts (Džermeikaitė et al., 2023).

AI APPLICATION IN FOOD SAFETY

The consumption of animal products is on the rise; this has prompted large-scale livestock farming and the supply chains that support it. Different researches are used to identify the key factors in livestock production that affect the quality of animal-derived products and the trials made to optimize all aspects of the quality. Along with an increase in the demand for food, the threat to food safety is growing, and, as a consequence, the problem requires strict control. The World Health Organization states that the protection of food quality and safety constantly increases the complexity for the food industry, as millions of people fall ill every year from contaminated food. The global economy suffers from tremendous social and economic loss due to the influence of substandard, falsified, contaminated, and adulterated food products. Traceability is regarded as a benchmark component

Table 5. Sensors used in movement, activity, and postural behaviors

Types of Sensors	Purpose of Sensors	References
Pedometers	Used for measuring the total distance travelled by an animal, along with the number of steps	Theurer et al., 2013
Radar-Based Sensors for Activity Behavior	Used for the assessment of activity behavior	Neethirajan, 2020
TIR (Thermal Infrared) Sensors	Used for the analysis of gait and the evaluation of the posture of walking	Harris-Bridge et al., 2018
Accelerometer Sensors	Helps in regular assessment of the movement, activity and change in behavior	Theurer et al., 2013; Neethirajan, 2020

Table 6. Sensors used for monitoring jaw movement

Type of Sensors used	Purpose of sensors	References
Pressure Sensors Acoustic Sensors Electromyography Sensors Accelerometer Sensors	Bite detection (number, rate, intensity and duration). Detection of jaw movement. Detection of grazing. Detection of animal behavior. Detection of duration and number of ruminations. Estimation of feed intake.	Neethirajan et al., 2017; Džermeikaitė et al., 2023

of food quality monitoring. The food traceability system involves collecting, storing, and transmitting all livestock history inside the Food Supply Chain (FSC), such as farm business, to assure the consumers about the quality, safety and can be traced backwards or forwards whenever needed. AI-driven Blockchain technology is a recent boom in food supply chain traceability (Patel et al., 2023).

Use of Blockchain Technology for Traceability

Blockchain technology creates a transparent, impermeable digital ledger that securely captures data related to animal health, milk production, supply chain operations, and financial activities within the livestock sector. Blockchain technology has shown to be groundbreaking in the domain of the food chain. The integration of blockchain technology into supply chains introduces features of decentralization, transparency, and trust. Transparency is one of the blockchain's success determinants, which means that every participant participating in the supply chain should be aware of every transaction that occurs (Khanna et al., 2022)

Information regarding the entire purchase or a specific dairy product is equally available to all interested parties (Feng et al., 2022). Other elements of blockchain success or application include safe data, a decentralized ledger, traceability, credible networks, smart contracts, quality assurance, automation, auditability, and the elimination of middlemen (Tsolakis et al., 2023). There are several layers in the supply chain model, including the phase, blockchain, traceability, and application layers. The phase layer consists of dairy farms, collecting locations, packaging and processing facilities, traders, and distributors. The dairy farm's website contains information on the animal's breed, amount of milk produced per animal, collecting facility, batch number, processing details, quality assurance check, and shelf life. The last phase consists of billing information, shipment data, and an adulteration check. The traceability layer enables stakeholders to track the movement of a given dairy product across the entire supply chain. The blockchain layer is the foundational layer of the system, providing all channels of communication between different supply chain participants. Firstly, stakeholders must register on the blockchain and then authenticate the transactions before initiating any transactions. The layer that communicates with retail consumers directly is known as the application layer. The end user establishes a connection with the system's application layer in order to utilize the functionality. As a result, the end user is provided with a comprehensive supply chain management system via the application layer. Scanning the QR code linked to the product provides the most updated information on its nutritional values (Khanna et al., 2022).

Limitations to artificial intelligence implementation:

There exist problems of different kinds that limit the AI adoption at the farm level or in the community, such as the technological, social and economic barriers. Technological barriers regarding AI-based systems are language interfaces, expert systems are unable to generate original solutions in unknown situations, to recognize an unfamiliar object or a situation, lack of flexibility and low ability to adapt to environmental changes and a high amount of data. Social barriers refer to AI being a risk to human life and its negative impact on cybersecurity and data privacy, the insufficient education and understanding, the mistrust of technology and the difference between AI developers and their consumers. Economic barriers are similar to limitations in terms of infrastructural and financial resources (Bačiulienė et al., 2023). In this issue, human resource obstacles are closely related to a lack of qualified workers and a deficiency of digital competence. On the other hand, customer-related barriers such as lack of security of the information, privacy violations and the support of the enterprise and production systems are related to the fear of losing control over their personal information.

FUTURE PERSPECTIVE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) has the potential to significantly improve animal health and management techniques in the future. Early diagnosis allows for timely treatments, which improve overall animal welfare and reduce disease transmission within herds or communities. Secondly, AI offers unparalleled capabilities in animal management. Artificial intelligence (AI) systems may monitor cattle conditions in real-time by using sensors, drones, and other Internet of Things (IoT) devices to identify any abnormalities in behavior, health, or environmental variables. This allows farmers and ranchers to take proactive measures to manage issues like stress, disease outbreaks, and nutritional deficiencies. Furthermore, AI plays

an important role in improving food safety by facilitating inspection operations and recognizing possible risks along the food manufacturing chain. Computer vision algorithms can be used to analyze the quality of animal products and to minimize the chances of contaminated food reaching the market. Moreover, AI-enabled systems trace the source of food products, assisting in identifying and eliminating the contaminated products and thus safeguarding public health (Zhou et al., 2022).

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