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AI-assisted disease diagnosis and health monitoring in livestock: Current applications, challenges, and future prospects

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Abstract

Diseases of livestock represent a significant constraint on livestock productivity, animal welfare and food security in many countries around the world, particularly in under-developed countries because of limited veterinary infrastructure and delayed disease diagnosis. Generally, conventional approaches of diagnostic tools have limited sensitivity, specificity, and scalability; and hence may fail to predict the disease risk at the herd level, leaving a significant void in the existing livestock health system. This article investigates the role of artificial intelligence (AI) in strengthening of the disease diagnosis in livestock, current capabilities, cross-species applications, and the most recent developments. A narrative literature review technique was utilized taking into consideration scientific studies, case studies, and evidence-based applications in species such as cattle, poultry, sheep, and swine. The key findings highlight the effective application of such AI techniques *viz.* deep learning, thermal imaging, gait analysis, audio monitoring, wearable biosensors, and GRU-based autoencoders in detection of mastitis, lameness, respiratory conditions, digestive problems, and reproductive events. The cross-regional comparison between Europe and South Asia revealed that the differences in AI adoption stem from imbalances in infrastructural, economic, and digital readiness. The study further outlines ethical concerns regarding data privacy, algorithmic bias, and animal monitoring. The integration of AI in livestock systems has the potential to revolutionize veterinary diagnostics and early detections of events, which would benefit the welfare of animals and ensure sustainable, precision livestock health management of animals across diverse farming contexts.

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1. Introduction

More than half of the estimated 40 billion livestock in the world live are kept in underdeveloped nations (Lane et al. 2025). In these underdeveloped nations, livestock play significant role in providing services related to economic growth, livelihoods, food security, and empowerment for women (Baltenweck et al. 2024; Naqvi et al. 2025). However, high disease prevalence has been observed in these underdeveloped nations. This hampers livestock production due to inadequate husbandry, feeding, and nutrition techniques, and limited access to routine veterinary services (Syamsu et al. 2024; Jawad et al. 2024). Further, poverty and zoonotic illnesses are closely linked, and the consequent effects are disproportionately seen in these poor nations (Grace and Cook 2023). Livestock production holds a global market value of approximately 2.57 trillion USD, comparable to global crop production (Schrobback et al. 2023). Livestock diseases negatively influence the animal production, increase treatment and control expenditure, and disrupt the trade in international and national markets (Kappes et al. 2023; Qayyum et al. 2025). In addition to the direct effects on livestock production and health, livestock diseases can affect humans and wildlife, particularly when the diseases involve zoonotic pathogens and interactions with environmental factors (Sarwar et al. 2024; Imtiaz 2025; Qamar et al. 2025). Often, these interactions take place by affecting the local habitats around livestock production sites (Kappes et al. 2023; Anuta et al. 2025).

Over centuries of husbandry and care, human-animal bonds have strengthened. Additionally, humans are morally obligated to ensure the psychological and physiological requirements of the animals and to minimize their inexplicable suffering. To fulfil these needs, access to veterinary services is crucial to maintain the well-being of animals (Pasteur et al. 2024). But not all regions have equal access to veterinary services due to challenges like lack of funds, inadequate transportation, lack of service providers or lack of one nearby, and cultural constraints that could lead to inequities (Lem 2019; Marcano et al. 2026). Current diagnostic methods face notable challenges, especially in terms of specificity and sensitivity, which hinder accurate disease identification. In the case of bovine tuberculosis, the tuberculin skin test is mostly employed as a diagnostic approach. However, the sensitivity of this test might varies with factors such as stage of infection, protocol followed, immune status of animal, resulting in occasional false results (Pasteur et al. 2024). This can lead to undetected cases, risking both humans and herds as well. Hence, such limitations stress the requirement of

additional diagnostic instruments with increased sensitivity to improve detection precision and support effective disease identification measures (Wang et al. 2021).

Conventional diagnostic imaging techniques, such as radiography, are limited in their ability to accurately assess soft tissues and identify minor lesions (Low and Peh 2017; Latif et al. 2024). The molecular diagnosis of infectious diseases also clearly shows technological limitations. For instance, PCR techniques do not distinguish between living and non-living organisms, despite their great sensitivity and specificity for viral DNA identification (Zeng et al. 2016; Rafique et al. 2024). Moreover, PCR-based techniques for diagnosing bovine mastitis are able to identify bacterial DNA in milk samples, but they are unable to differentiate bacterial contamination from infection in its active state (Gulyukin et al. 2025). Consequently, these limitations increase the chances of misdiagnosis, thereby contributing to inappropriate and excessive antibiotic use (Kajdanek et al. 2024; Alfifi 2025; Rizqan et al. 2025). The traditional approaches result in errors, such as false positives and false negatives, and may not take individual variances into account (Bouchemla et al. 2023). So, to ensure precise disease diagnosis and efficient management strategies, diagnostic tools must be designed with a proper balance between sensitivity and specificity (Ochwo et al. 2023).

In efforts to improve disease surveillance, technological innovations have been developed that enable the automated and direct assessment of health and welfare (Fig. 1). AI has transformed various fields such as agriculture and medicine in a number of ways, including highly productive crops, better diagnosis and therapy, with encouraging outcomes in a range of medical services through offering precise and effective diagnostic capabilities (Irfan et al. 2024; Shafiq et al. 2024; Amer and Amer 2025; Tariq 2025). AI strengthens diagnostic precision and predictive capabilities, which benefits animal healthcare (Bouchemla et al. 2023; Ali et al. 2025a). AI has the potential to enhance the healthcare system by optimizing resource utilization, enhancing healthcare accessibility, and enhancing treatment quality (Endo et al. 2024). It has potential applications veterinary medicine, especially in improving diagnostic accuracy, including medical imaging, disease-risk prediction, and telemedicine (Prakash 2024). This review aims to explore the recent landscape and future directions of AI-assisted disease diagnosis in livestock, with an emphasis on cross-species applications, technological catalysts, current limitations, and subsequent applications.

2. Literature review and data analysis

A narrative literature review was utilized for writing this manuscript. Literature searches were done across Google Scholar, PubMed, Scopus, ScienceDirect, and ResearchGate. Articles published

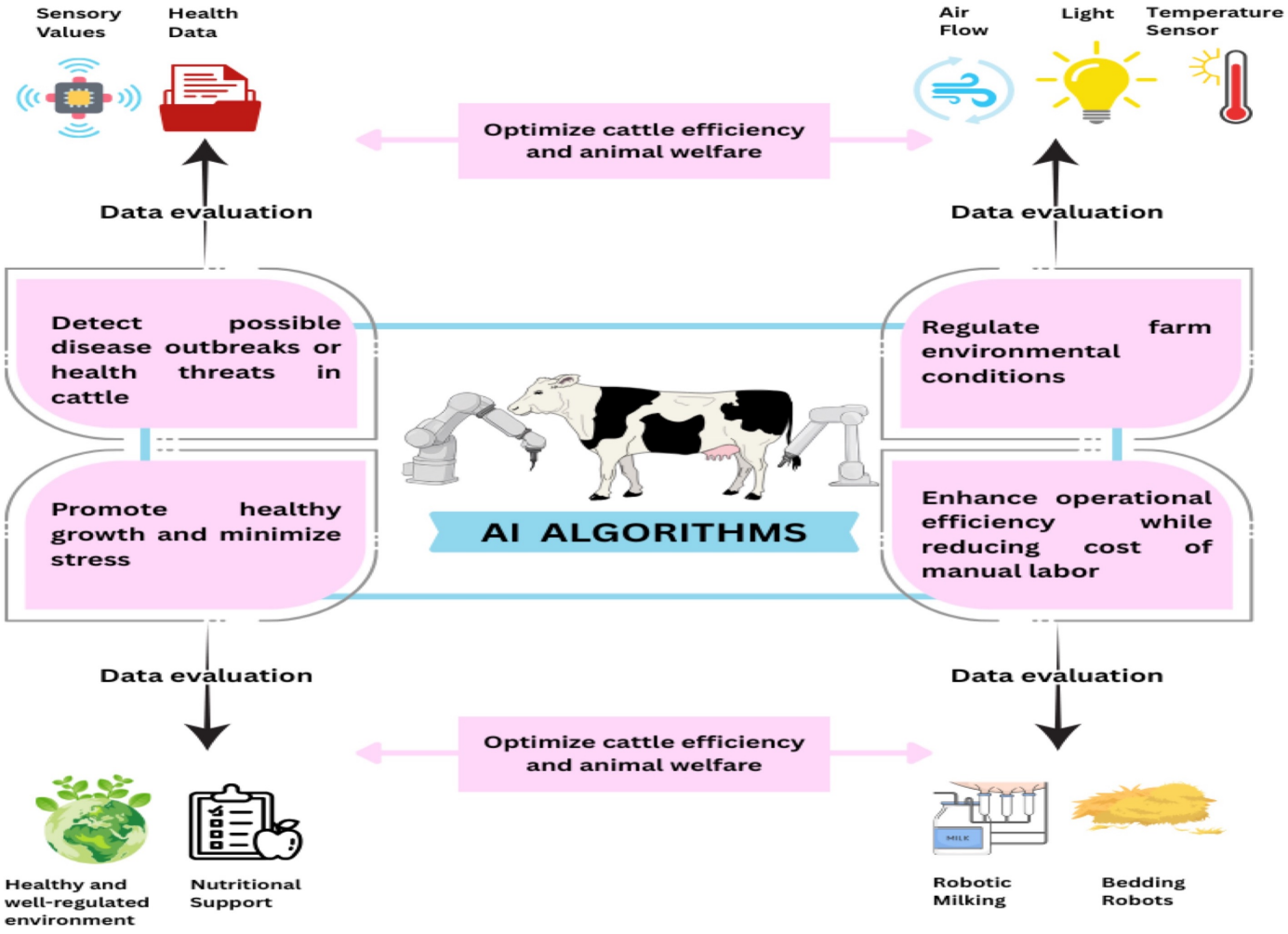


Fig. 1. *General workflow of AI-assisted disease diagnosis in livestock and its role in optimizing cattle welfare*

between 2006 and 2026 were included, with majority of sources published from 2020 to 2026 to show the current advances of AI in livestock health. The search included the following keywords: ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, DEEP LEARNING, SENSOR TECHNOLOGY, PRECISION LIVESTOCK FARMING, WEARABLE BIOSENSORS, THERMAL IMAGING, DISEASE DIAGNOSIS, AND HEALTH MONITORING. These searches were combined with species-specific terms such as cattle, poultry, sheep, and swine. Studies reporting AI, sensor, or technology relevant to livestock were included. However, articles not related to livestock and inaccessible studies were excluded. Initially, titles and abstracts were screened for relevance. Selected articles were evaluated using their full texts; the abstracts were used when full texts were not available.

3. AI technologies and data sources in livestock

AI-assisted disease diagnosis in livestock depends on a wide range of technologies and data sources to identify health problems accurately and at an early stage. These systems integrate data from imaging devices, wearable sensors, thermal cameras, acoustic monitoring systems, and Internet of Things (IoT) devices with machine-learning and deep-learning algorithms to support timely and precise diagnosis (Hafsa 2025). Their effectiveness mainly depends on the computational techniques and quality of the input data. The common AI methods used for livestock disease diagnosis are presented in Fig. 2.

3.1 Machine learning (ML)

Machine learning (ML) enables computer systems to identify patterns from data without direct programming. These models analyze data and make predictions based on what they have learned (Razzaq and Shah 2025). Commonly used ML-based algorithms in livestock include Support Vector Machine (SVM), Random Forest, Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, Linear Regression, and Naive Bayes for disease prediction and health monitoring. Unsupervised methods such as K-Means Clustering and Principal Component Analysis (PCA) are also used for pattern recognition and data analysis (Mia et al. 2025). ML is transforming livestock farming by analyzing data from sensors, cameras, wearable devices, and environmental monitoring systems to support accurate decision-making (Vlaicu et al. 2024). It assists in early disease detection, monitoring animal behavior and welfare, improving feeding schedules, reproductive management, and ecological conditions. It may also supports productivity and reduction of disease outbreaks. ML plays a role in precision livestock farming by using resources efficiently to enhance sustainability (Mishra and Mishra 2023). ML can analyse imaging and sensor data to assess product-quality traits and monitor food safety and traceability (Chhetri 2024). Overall, ML enhances efficiency, animal welfare, and the quality of livestock products.

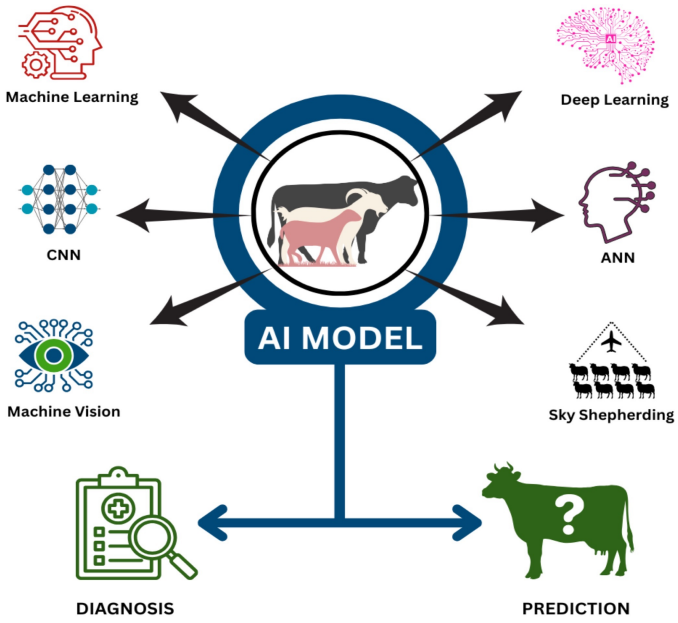


Fig. 1. Common AI models applied in livestock disease diagnosis and health monitoring

3.2 Deep learning (DL)

Deep learning (DL) is an advanced type of machine learning that learns patterns from large amounts of complex data sets (Chen and Chen 2026). In livestock management, DL models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, ResNet, VGGNet, GoogLeNet, YOLO, U-Net, and Vision Transformers (ViTs) are used for disease diagnosis and prediction (Xiao et al. 2025). These models have the ability to analyze images, videos, sensor data, and farm records to detect diseases precisely. CNNs are mainly used for image analysis, while RNNs and LSTM networks are suitable for sequential data that include sensor readings (Ahmadzadeh et al. 2025). Pretrained models may improve performance when limited training data is available. However, DL models require large, high-quality datasets and proper validation to ensure accurate and reliable disease diagnosis (Shah et al. 2026).

3.3 Computer vision

Computer vision is a branch of AI that enables the computers to access, process, and interpret visual information from images and videos (Wu et al. 2025). In livestock farming, it provides a non-invasive and automated approach for monitoring animal health. It also helps in estimating disease risk (Antognoli et al. 2025). Computer vision systems use cameras, drones, and deep learning models to detect visible signs of disease, monitor body condition, assess lameness, estimate body weight, identify estrus, and evaluate feeding, drinking, and respiratory behaviors (Islam et al. 2026). By consistently analyzing visual data, these models support early disease detection and reduce the need for manual observation. Hence the accuracy and efficiency of livestock health monitoring improves.

3.4 Wearable sensors and biosensors

Wearable sensors and biosensors are emerging AI based technologies that monitor the health and behavior of livestock in real time. They potentially help detect diseases early by collecting continuous information without harming the animals. Wearable devices like smart collars, accelerometers, rumination sensors, temperature sensors, and heart rate monitors record physiological and behavioural activities, helping assess overall animal health (Ding et al. 2025). Biosensors detect specific pathogens or biological markers and convert these responses into measurable signals to provide rapid and accurate disease diagnosis of diseases such as African swine fever, Brucella, avian influenza, and *Toxoplasma gondii* (Zhao et al. 2025). Together, these technologies improve early disease detection, timely intervention, animal welfare, and livestock management.

3.5 Internet of Things (IoT) and Smart monitoring

Internet of Things (IoT) is a network of connected devices that collect, transmit, and analyze data through the internet. It consists of sensors, microcontrollers, communication modules, cloud platforms and mobile/web applications for optimized remote monitoring (Raza et al. 2025; Dwivedy et al. 2026). In livestock systems, IoT enables continuous or periodic remote monitoring of animal health, behavior, and environmental conditions. It works by integrating wearable sensors, cameras, and other smart devices to collect real-time data on body temperature, heart rate, activity, rumination, and location (Assaad et al. 2025). The collected data may be transmitted to cloud-based platforms, where AI algorithms analyze them to detect diseases early, identify abnormal behavior, and generate real-time alerts for farmers and veterinarians (Modak et al. 2025). This technology improves disease surveillance and supports timely intervention to enhance livestock health and farm productivity (Ahmad et al. 2025).

3.6 Acoustic monitoring

Acoustic monitoring is a non-invasive technique that records and analyzes animal sounds to assess their health and behavior. It uses microphones and sound sensors to continuously monitor livestock without disturbing the animals (Ramos Niño et al. 2025). The system typically involves sound recording, preprocessing (noise filtering), sound labeling, feature extraction, and AI-based classification. Common acoustic features include power spectral density (PSD), spectral and temporal features, zero-crossing rate (ZCR), and mel-frequency cepstral coefficients (MFCCs) (Reza et al. 2025). Acoustic monitoring analyzes coughs, sneezes, grunts, squeals, breathing sounds, and distress to detect respiratory diseases, stress, pain, and other health disorders (Kapetanidis et al. 2024; Reza et al. 2025). This allows early disease diagnosis and better livestock care.

3.7 Thermal imaging

Thermal imaging, or infrared thermography (IRT), is non-invasive imaging technique that detects infrared radiation emitted from the body to measure surface temperature. It produces thermal images that help identify abnormal surface temperature changes associated with certain diseases (Korelidou et al. 2024). Specifically in livestock, thermal imaging is used to detect fever, inflammation, mastitis, lameness, foot-and-mouth disease, respiratory infections, and other health abnormalities before clinical signs become visible. It enables rapid, contact-free disease screening and improves the accuracy of disease diagnosis for improved animal welfare and increased farm productivity (McManus et al. 2022).

3.8 Data integration (Multimodal AI)

Multimodal AI combines information from multiple data sources to provide a more comprehensive evaluation of livestock health. It integrates different types of data to improve the accuracy and reliability of disease diagnosis (Wen et al. 2025). In livestock, multimodal AI combines medical images, behavioral videos, audio recordings, clinical notes, laboratory results, and sensor data using early fusion, late fusion, and hybrid fusion strategies. Integration of these data together may improves diagnostic accuracy and clinical decision-making than single-data source approaches (Gomes et al. 2025). These AI technologies and data sources collectively are the backbone of recent livestock disease diagnosis as they are able to analyse various kinds of data which helps in early, timely and accurate diagnosis of disease and hence better management of animal health.

4. Applications of AI in disease diagnosis

4.1 Disease-specific models

4.1.1 Mastitis: Image-based AI, SCC diagnosis

Mastitis is among the most common diseases affecting dairy cows and small ruminants globally, resulting in significant direct and indirect economic losses (Ahmad and Nawaz 2024). These losses include reduced milk production, increased treatment cost, and premature culling of infected animals (Susanty et al. 2025). Moreover, the emergence of large-scale dairy production resulted in large volumes of data, highlighting the need for AI-based tools to diagnose and monitor the prevalence of mastitis (Ebrahimi et al. 2019). AI can integrate milk production records, sensor measurements, and clinical observation to support early disease detection. Machine learning (ML) has been applied to detect and diagnose both clinical and subclinical forms of mastitis (Luo et al. 2023). Algorithms such as support vectors machines and decision trees can analyze multiple diagnostic indicators to differentiate healthy animals from the infected ones. Studies highlight the use of artificial neural networks (ANNs) and random forest models as the most effective classifiers. However, their performance depends on dataset quality, diagnostic accuracy, and validation under different farm conditions. For the diagnosis of both clinical and subclinical mastitis, SCC continues to be the most important biomarker (Aftab et al. 2024; Mitsunaga et al. 2024). Combining SCC with milk yield, electrical conductivity, and other sensor-based measurements may further improve diagnostic accuracy. Infrared thermal imaging, integrated with deep learning models such as YOLOv5, has shown significant potential in the detection of mastitis (Wang et al. 2022a). Thermal imaging provides a non-invasive method for detecting udder temperature changes associated with inflammation. Other diagnostic methods including bacterial culture and PCR for pathogen identification, the California Mastitis Test for on-farm screening, and clinical examination for detecting visible abnormalities. Although SCC and electrical conductivity are useful for monitoring and observation of udder health. They cannot independently confirm bacterial infections. Combining these conventional methods with AI-based approaches may improve early detection and diagnostic accuracy, while culture and PCR can support pathogen identification when required.

4.1.2 Lameness: Gait detection using motion analysis

Lameness in dairy animals has a significant adverse impact on both the economy and animal welfare (Suarez et al. 2025). Traditional analysis rely on manual or visual based techniques by gait or locomotion scoring, which may be subjective (Leach et al. 2009; Dutton-Regester et al. 2020). Hence, the use of AI-powered gait analysis to diagnose lameness in cattle and other livestock continues to rise. Deep learning models, such as YOLOv8 and Mask-RCNN, have been used to detect and track cattle for automated lameness detection in video sequences. Machine learning classifiers like AdaBoost, SVM, and Decision Trees were then used to analyze lameness based on retrieved features (Myint et al. 2024). Another approach suggested a Siamese attention model (Siam-AM) to automatically track the movement of cow legs using motion patterns in video images. Leg movement data is then used to classify lameness using a Support Vector Machine (SVM). This model achieved more than 90% accuracy for both lameness detection and tracking, recognizing its potential for large-scale automated farm monitoring (Zheng et al. 2023).

4.1.3 Respiratory Illnesses: Audio and thermal input

In livestock, respiratory diseases including pneumonic pasteurellosis and bovine respiratory disease (BRD) are serious health concerns globally (Abera and Mossie 2023; Pratelli et al. 2024). In order to lower mortality, treatment cost, and antibiotic overuse, early detection and diagnosis are critical. AI-based monitoring facilitates earlier disease diagnosis than conventional methods by detecting even minor changes in respiratory patterns without time constraints (Neethirajan and Kemp 2021; Bao and Xie 2022). AI can differentiate between infections and detect specific diseases in pigs, such as Mycoplasma hyopneumoniae, Postweaning Multisystemic Wasting Syndrome, and Porcine Reproductive and Respiratory Syndrome (Chung et al. 2013; Hong et al. 2020). Infrared thermography (IRT) of the eye has been shown to detect bovine respiratory disease several days before clinical signs appear. When integrated with RFID-triggered camera systems at water stations, it facilitates non-invasive and automated disease detection, eliminating the need for physical restraint and manual sampling (Jeelani and Jeelani 2019). SoundTalks, a commercially available AI-based technology, monitors respiratory health condition of livestock by recognizing and analysing cough sound patterns. It also features sensors to track things like relative humidity and room temperature. Additionally, it contains an alert mechanism that notifies sudden temperature fluctuations and possible respiratory issues (Lagua et al. 2023).

4.1.4 Digestive disorders: Rumination sensors and monitoring belts

In the cattle industry, rumen bolus sensors present considerable potential due to their secure positioning within the animal accompanied by durable battery life, making them potentially appropriate for continuous health monitoring. They are typically designed to monitor three main parameters including rumination, temperature, and rumen pH. These boluses can track the drinking behaviour of cattle and help in examining how the drinking pattern is affected (Hajnal et al. 2022). The ability to monitor ruminal temperature and cow's behavior can help with the early detection of inflammatory conditions and the estrous, thereby supporting effective herd management (Burnett et al. 2020; Carroll 2024; Ali et al. 2025b). Also, a smart wearable belt has been developed for effective cow health monitoring. It measures stomach size precisely to monitor pregnancy, ensure nutrition, regulate breeding, evaluate stress, and predict or diagnose digestive problems earlier; however, independent validation is required for each proposed application. Additionally, a GSM system (arduino-based) is integrated in this belt for prompt responses by providing alerts (Vaishnavi and Rahul 2024). Thus, these AI modules improve cattle health and farm productivity.

4.2 Cross-species and region-based AI

AI-based tools are used in disease surveillance, using resources sustainably, planning farms, and taking care of animals (Hamadani et al. 2024). AI has wide range of applications in livestock welfare and health across species (Table 1) with outstanding approaches created to address the unique requirements of cattle, poultry, and sheep. In dairy animals, different AI learning methods like random forest, eXtreme Gradient Boosting (XGBoost), naïve Bayes, decision tree induction, logistic linear mixed models, and neural networks are used to predict or identify clinical mastitis and other health problems (Kamphuis et al. 2010; Ankinakatte et al. 2013; Khatun et al. 2018; Fadul-Pacheco et al. 2021). Machine learning algorithms have been applied for early detection and treatment of metritis and monitoring of the metabolic conditions in dairy cows, especially during early lactation phase (Džermeikaitė et al. 2025; Girdauskaitė et al. 2025). In poultry, robots can perform various functions like egg collection and transport, automated feeding, environmental monitoring (temperature and humidity), behavior tracking, and poultry house cleaning (Özentürk et al. 2023). AI-based age estimation in poultry can enhance farm management by providing precise and timely information about bird age when it is not reliably available from the farm records. It can also classify chick calls for sex determination (Guo et al. 2022; Taleb et al. 2025). Non-invasive infrared thermal imaging monitors surface body temperature. This potentially identifies surface temperature changes associated with illness but fever prediction may require proper validation (Karaarslan and Nazlıgül 2024). Similarly, the AI-based analysis have been explored to assess the histological data from the research on murine intervertebral disc (IVD) degeneration animal model and this method holds potential for diagnosing degenerative IVD conditions in sheep (Alini et al. 2023). Additionally, deep learning modules have made it possible to predict earlier detection of respiratory diseases in ovine species (Arshad et al. 2024). AI-based tools are being used for a variety of livestock species, such as goats, pigs, horses, lambs, and poultry. However, it is necessary to figure out aspects of tools designed for one species in order to fit another (Arshad et al. 2024; Melak et al. 2024).

4.3 AI in Europe vs South Asia

There are notable regional differences in the application and impacts of AI on livestock health. In European production systems, precision livestock farming (PLF) has been widely adopted compared to South Asian regions (Jiang et al. 2023). PLF tools provide the collection and evaluation of data, which include sensors, cameras, and auditory devices that are incorporated with artificial intelligence. It enables farmers to predict and detect stress symptoms at initial phase (Papakonstantinou et al. 2024). Reliable internet access, appropriate funding, and social capital encourages AI development and successful adoption (Kopler et al. 2023). Conversely, South Asian regions have more complex and challenging conditions especially due to low socio-economic status (Rasul et al. 2021). Also, broad implementation of AI is hindered by technological complexity, data security, and challenges in adaptability across different regions (Issa et al. 2024). However, low-cost sensors, cloud-enabled diagnostic tools, and mobile applications have the potential to bridge this gap (Ngo et al. 2020; Senthilkumar et al. 2021; Asmare 2022). Further, AI tools are trained using data from specific regions and may not perform equally well in other regions (Arshad et al. 2024). So, for AI to be truly impactful, cross-regional collaboration is essential to ensure its benefits reach both developed and underdeveloped livestock regions.

5. Current limitations and ethical considerations

Without a doubt, artificial intelligence can be quite useful in diagnosing livestock diseases but there are numerous impediments to widespread usage. Therefore, reservations related to data handling and security, adoption by small-scale farmers, and ethical and social implications must be addressed. Adoption of AI may not be beneficial for small-scale farmers because it requires large and high-quality datasets, high-end equipments, technical expertise for accurate monitoring and prediction. But small farms often do not have good data, and that is why there are inconsistent results. Additionally, the use of AI equipment requires

Table 1. Cross-species applications of AI techniques for disease diagnosis and health monitoring in livestock

Application area	Species	AI technique	Input data	Primary outcome	Performance metrics	References
Mastitis detection	Cattle	Naive Bayes, DLM, DL, GBT	Milk yield, conductivity, fat, protein, SCC	Early alerts for subclinical and clinical mastitis	84.9% accuracy for GBT	(Jensen et al. 2016; Ebrahimi et al. 2019)
Tuberculosis diagnosis	Cattle	CNN	Mid-infrared (MIR) milk spectra converted to images	Automated early TB detection with	95% accuracy	(Denholm et al. 2020)
Estrus Detection	Cattle	Backpropagation Neural Network	Behavioral features (e.g., lying, steps, mounting)	Detect onset of estrus for timely breeding	95.4% accuracy	(Wang et al. 2022b)
Calving Prediction	Pregnant Cows	RF, LDA, Neural Networks	Activity data from neck collars	Prediction of calving within 24 hours	100% sensitivity by neural networks	(Borchers et al. 2017)
Conception Prediction	Cattle	Logistic Regression, RF	Health & repro history, BCS, MIR spectra	Identify high fertility cows	85% conception rate in top 10% ranked	(Shahinfar et al. 2014; Hempstalk et al. 2015)
Milk Yield Forecast	Cattle	ANN, DL	Past lactation data, nutrition, genetics	Daily and total milk prediction for herd management	High accuracy in first 26 days of lactation	(Grzesiak et al. 2006; Liseune et al. 2021)
Feed Intake Monitoring	Cattle	ML, RGB-D Camera, Object Tracking	Feed trough video, cow ID, disappearance rate	Estimate individual cow feed intake	Mean absolute error = 0.12–0.14 kg	(Lassen et al. 2018; Saar et al. 2022)
Pregnancy Risk via BCS	Cattle	Logistic Regression	BCS at key intervals, health	Predict pregnancy likelihood (PI)	Camera vs manual r = 0.7–0.78	(Pinedo et al. 2022)
Respiratory Disease Detection	Pigs	DL, GRU-based Autoencoder, PSO Optimization	Environmental sensor data (temperature, humidity, gases)	Early detection of PRRS-related anomalies up to 7 days in advance	Precision = 0.776	(Cowton et al. 2018)
Intervertebral Disc Diagnosis	Sheep	ML-based Histological Analysis, Image Analysis	Histopathological slides, spinal imaging data	Identification of therapeutic targets, pain assessment	High sensitivity and specificity	(Alini et al. 2023)
Automated Bodyweight Tracking	Sheep	WoW, RFID, Statistical Modeling	Pressure sensor data, RFID tags, animal behavior logs	Precise daily body weight monitoring	Concordance correlation coefficient = 0.89–0.98	(González-García et al. 2018)
Bird Flu Virus Detection	Poultry	SVM	Image data of broilers	Provision of early warning alerts	~ 99.5% accuracy	(Zhuang et al. 2018)
Respiratory Disease Detection	Poultry	CNN	Cough sound patterns	Identifying infectious bronchitis and Newcastle disease	98.4% and 92.6% accuracy respectively	(Mbelwa et al. 2021)

strong investment and skills which many small farmers may not have. Hence, ensuring access to these advanced technologies always remains a major barrier (Arshad et al. 2024). Privacy was considered solely a human concern previously. Now, it has gained new significance in the context of livestock systems. (Mahato and Neethirajan 2024). Surveillance of livestock on a regular basis tends to raise numerous ethical issues. Although real-time monitoring and wearable sensors are valuable tools to monitor health, they can impact the regular habits of animals, comfort, and social interactions also. Animals cannot give informed consent like humans. Therefore, the responsibility lies on farmers, technology developers, and policymakers to set clear limits in terms of the effects on the animal welfare. It is important to balance the benefits of AI-based health monitoring against invasive tracking-induced potential animal welfare cost. In order to minimize excessive interference with animal behaviour, clear ethical rules must be developed to make sure these technologies mainly focus on animal well-being (Liu et al. 2020). The use of sensors and AI generates large amounts of farm-related data, which includes genetic details, health records, and behaviour traits. Therefore, data protection and ownership issues are raised because there is a high risk of data leaks which can affect farm's reputation and position in the market. Hackers can exploit poorly secured AI systems to access and collect confidential information (Congdon et al. 2022; Hernandez et al. 2022). Moreover, many deep learning models function as "black boxes" that have limited interpretability and raises several concerns. When AI makes decisions without clear justifications, it may be hard to establish the accountability for the resulting decisions. This creates problems when outcomes are harmful or raise ethical conflicts. The trustworthiness and objectivity of AI systems depend on the quality and diversity of the data they are trained on. This data may result in AI-based judgments against particular animals or favoring specific approaches which could have consequences. Additionally, AI-based advice and judgments must be trusted by farmers, veterinarians, and other animal production stakeholders (Congdon et al. 2022; Neethirajan 2024).

6. Future prospects and emerging directions

The emergence of artificial intelligence is generating new opportunities for livestock disease prediction, diagnosis, and health management. AI has shown major advancements across multiple industrial sectors (Saida et al. 2025). On top of that, there is an increased likelihood of its potential to expand in future (Vâtcă et al. 2021). As AI evolves, the development of novel and more robust algorithms is expected to emerge (Raza et al. 2023). By adopting modern innovations and AI, farmers can improve livestock health and promote better animal

welfare (Congdon et al. 2022). In the future, video analytics may be used in the dairy industry to automatically check if workers are following standard procedures. Instead of employing punitive methods, the ultimate goal would be to motivate training and progress. Real-time language translation presents another opportunity, which is particularly beneficial for groups of workers who speak multiple languages. Tutorials and spoken guidance can be translated into the languages that staff members are most familiar with. Significant enhancements in AI-assisted translation have been made in the past few years (Wang et al. 2022c).

7. Conclusions

The use of AI is shifting the standards used to diagnose diseases in livestock by providing the opportunities to transition out of reactive health care and into predictive health care based on quality data. AI models such as deep learning, image recognition, sensor-based analytics, and behavior monitoring are now used to identify a variety of illnesses in various species faster and more accurately than previously. This includes mastitis, lameness, respiratory disorders, and digestive disorders, among others. The application of AI in livestock systems not only makes the diagnoses more accurate, but also guarantees animal well-being, reduces the dependence on antibiotics, and may enhance sustainable livestock management by providing timely decisions. Although AI has massive potential to revamp the livestock systems, it is still hampered by a number of its major challenges. Privacy concerns with the data, ethical behavior of constantly monitoring the animals, and the opacity of some AI algorithms are the obstacles. Also, infrastructure differences, digital literacy, and access to resources further hinder its adoption. These challenges are particularly eminent in low-income and middle-income economies where the access to technology and finances is limited. Addressing all these obstacles needs management through collaboration between veterinarians, researchers, policymakers, and farmers. It is essential to construct area-specific data sets, create transparent AI systems, and develop smart technologies more affordable and accessible. Through intelligent deployment and responsible management, AI has the potential to transform the way diseases in livestock are diagnosed and set the basis of achieving a more sustainable, equal, and animal-welfare-friendly future across all corners of the globe.

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