Survey on Machine Learning and Deep Learning Applications in Livestock and Biomedical Research[1]

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Abstract

Machine learning (ML) and deep learning (DL) have emerged as transformative technologies across livestock and biomedical research, enabling advances in disease detection, animal health monitoring, genetic selection, and reproductive evaluation. In dairy production, ML/DL techniques have enhanced the early diagnosis of subclinical mastitis [9]; [19]; [48], lameness [2]; [29]), and infectious diseases in calves ([12]), offering non-invasive and cost-effective alternatives to traditional methods. These technologies have also improved genomic prediction strategies, combining deep learning with genomic BLUP frameworks ([21]; [33]) and providing explainable classifiers based on whole-genome sequencing ([19]). Furthermore, DL has been successfully applied to cattle identification [3]; [28]; [41]), feeding behavior monitoring [4]; [49]), reproductive assessment of bovine oocytes ([34]; [5], and carcass quality grading ([20]; [17]; [23]). Beyond livestock, biomedical research has benefited from DL in medical imaging, genomics, and disease surveillance ([14]; [18]; [47]). Despite remarkable progress, challenges remain in terms of data quality, generalization across farms, interpretability, and ethical implications ([30]; [35]; [32]). By integrating AI with precision livestock farming and biomedical practices, interdisciplinary collaboration can foster more sustainable, accurate, and welfare-oriented systems.

Keywords: Machine learning, Deep learning, Precision livestock farming, Genomics, Disease detection, Computer vision

Introduction

In recent years, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has transformed the landscape of livestock management and biomedical research. These computational techniques are capable of processing massive heterogeneous datasets, extracting complex nonlinear patterns, and generating accurate predictions that were previously unattainable with conventional statistical methods. Their impact has been particularly significant in areas such as animal health monitoring, reproductive management, genetic selection, behavioral analysis, and food quality assessment ([45]; [9]; [42]; [19]).

One of the most relevant applications of ML and DL in dairy farming is the early detection of diseases. Subclinical mastitis, a highly prevalent and costly condition, has been widely studied through predictive modeling. Gradient-boosted trees and deep neural networks have consistently outperformed traditional linear models, offering accuracies above 80% in large-scale datasets [9]. More recent advances incorporate genomic information, such as whole-genome sequencing combined with explainable DL

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classifiers ([19]) or multilayer perceptrons adjusted to different somatic cell count thresholds ([48]). Complementary methods such as Fourier-transform infrared spectroscopy ([40]) and MALDI-TOF mass spectrometry ([38]) further demonstrate the versatility of AI-driven diagnostics. Similarly, lameness—another critical welfare issue—has been addressed using pose estimation, side-view video analysis, and automated gait detection systems, achieving reliable results under commercial farm conditions ([2]; [29]; [37]).

AI has also revolutionized livestock identification and monitoring. Traditional RFID-based and ear tag systems are increasingly being complemented or replaced by computer vision approaches. Biometric recognition through facial imaging has proven highly accurate in real-time herd management [3]; [28]), while skeletal key-point detection and pose-based tracking methods provide alternatives when facial images are not available ([43]; [27]; [16]). These methods enhance traceability and reduce reliance on manual labor, improving management efficiency in large herds [6]; [50]). In addition, behavior monitoring systems based on CNNs and hybrid CNN–RNN architectures have been applied to detect regurgitation ([11]), classify daily activities such as feeding, walking, and lying (Yu et al., 2024; [22]), and optimize feeding schedules [4].

Reproductive technologies are another field where DL has shown significant contributions. Traditionally, embryo and oocyte quality assessments relied on subjective evaluations by embryologists. However, DL models now provide automated, objective, and reproducible quantification of bovine oocyte cumulus expansion and embryo viability, with strong correlations to developmental outcomes [5]; [34]). These advancements reduce variability, accelerate decision-making, and support in vitro fertilization programs with higher accuracy.

In parallel, genomic prediction has advanced through the integration of ML and DL. Frameworks such as deepGBLUP combine DL architectures with genomic best linear unbiased prediction, significantly improving the accuracy of complex trait prediction in cattle ([21]). Genomic-based DL classifiers have also been developed to predict mastitis susceptibility, leveraging explainable AI to highlight key genetic markers ([19]). Further, cross-species enhancer prediction models ([25]) and sensor-derived trait integration ([33]) demonstrate the expanding role of AI in genomics and precision breeding.

At the production chain level, DL applications extend to carcass quality assessment and meat safety. Convolutional neural networks have been applied to automate beef marbling scoring ([20]), identify adulteration with colorants or curing agents using spectroscopy ([17]), and predict freshness with low-cost colorimetric sensors ([23]). Similar approaches in pork production focus on limb detection and robotic gripping for industrial automation, reducing human labor and ensuring standardization in meat factories ([26]).

The versatility of AI is further demonstrated by its application in biomedical sciences. Techniques developed in livestock contexts, such as computer vision and DL-based imaging, are being translated into medical applications. Examples include label-free optical coherence tomography imaging of lymphatics and aqueous veins ([14]), hyperspectral fluorescence imaging assisted by DL ([18]), and the use of remote sensing data combined with DL to track schistosomiasis sources ([47]). These examples highlight the reciprocal influence of biomedical and livestock AI research, where advancements in one field stimulate progress in the other.

Nevertheless, several challenges limit the large-scale adoption of ML and DL in agriculture and biomedicine. Data fragmentation, heterogeneity, and limited availability restrict model generalization across farms and populations ([30]; [33]). High computational costs and limited access to infrastructure hinder adoption by small- and medium-scale farms ([2]). Ethical considerations also emerge, particularly regarding animal welfare, data privacy, and the risks of over-monitoring or exploitation ([32]; [35]).

Addressing these issues requires interdisciplinary collaboration among veterinarians, engineers, computer scientists, and policymakers to ensure transparent, explainable, and welfare-oriented AI systems.

In this context, this study provides a comprehensive survey of ML and DL applications in livestock and biomedical research. By systematically analyzing state-of-the-art contributions, it identifies key trends, methodological advances, and future opportunities for sustainable adoption. Ultimately, the integration of AI into precision livestock farming and biomedical sciences has the potential to improve productivity, animal welfare, and public health simultaneously.

Methodology: Systematic Mapping Study and VOS Viewer Analysis

In conducting this survey on the application of artificial intelligence and deep learning in livestock farming, a **Systematic Mapping Study (SMS)** was applied to ensure a comprehensive and structured approach to document selection. SMS is a methodology designed to classify and categorize existing research across a wide area, offering an overview of the trends, gaps, and research focus in a given field. It provides a high-level understanding of where the research is concentrated and helps identify both well-explored and under-investigated areas.

Systematic Mapping Study Process

The SMS process followed three main phases: planning, conducting, and reporting. During the planning phase, research questions were defined to guide the study. The focus was on the application of AI in livestock farming, covering aspects such as animal welfare, disease detection, productivity optimization, and behavioral analysis. The scope was deliberately broad to capture the diverse research activities in this field.

- *Search and Selection:* a set of predefined search terms was applied to various academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Web of Science. These search terms were structured around keywords such as "artificial intelligence," "deep learning," "livestock farming," "animal welfare," and "precision agriculture." The inclusion criteria targeted peer-reviewed articles published between 2015 and 2024 that directly addressed AI applications in livestock farming. Articles focusing on conceptual frameworks without empirical data or specific applications were excluded from the study.
- *Classification Scheme:* once the articles were retrieved, they were categorized based on their research focus. Categories included topics like disease detection, animal behavior analysis, health monitoring, and productivity enhancement. Each study was classified according to its methodology, application area, and the type of AI technique employed (e.g., machine learning, computer vision, or sensor data analysis).

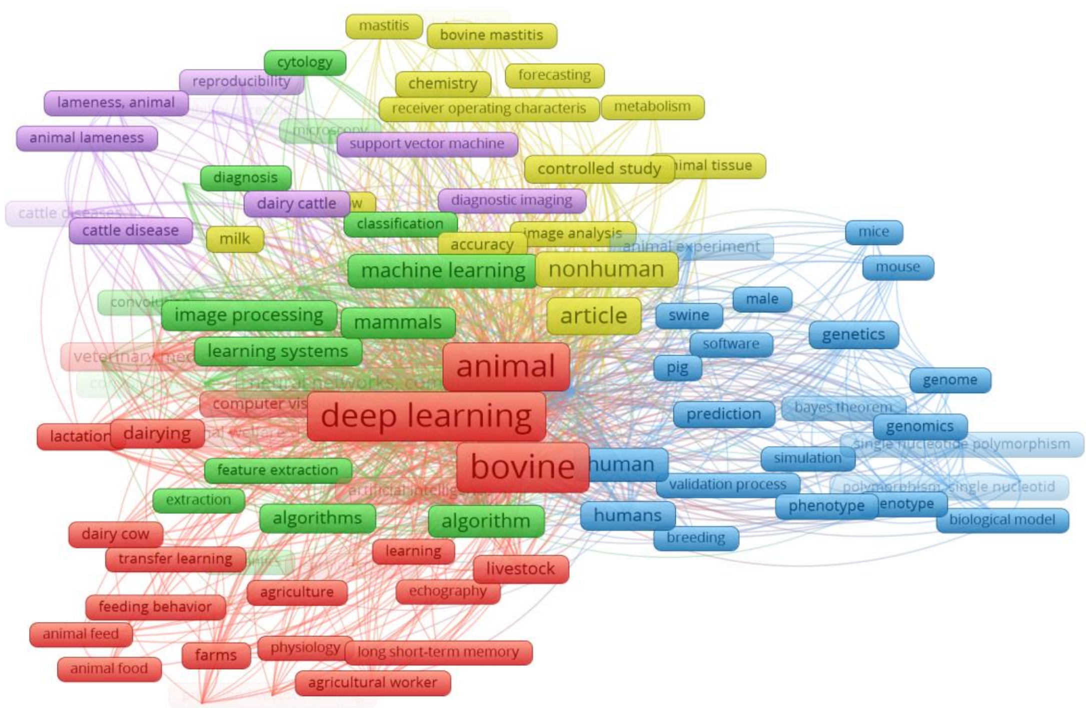
VOS Viewer Interpretation

To complement the SMS process, a **VOS Viewer** analysis was conducted to visualize and interpret the bibliographic data. VOS Viewer is a powerful tool used for constructing and visualizing bibliometric networks, allowing for the identification of relationships between research topics, authors, and key terms in a given body of literature.

Using the VOS Viewer software, a co-occurrence network of keywords and terms was generated from the selected documents. The analysis revealed clusters of research activity within the AI and livestock farming space, highlighting the most frequently addressed topics and emerging trends.

- *Cluster Analysis:* the VOS Viewer identified several key clusters. For instance, one cluster was centered on disease detection and animal health monitoring, a theme that featured prominently in works such as Ghaffari et al. (2022) and Wang et al. (2022). Another major cluster focused on precision agriculture and optimization of farm management, underscoring the potential of AI for enhancing overall productivity. These clusters demonstrated that health monitoring and precision management were dominant areas in current AI research in livestock farming.
- *Term Frequency and Connections:* In addition to the cluster analysis, VOS Viewer helped map the relationships between terms such as "animal behavior," "machine learning," "deep learning," and "computer vision." This network visualization made it clear that AI applications in livestock farming are heavily driven by machine learning and computer vision technologies, a finding consistent with the broader trends observed in the SMS.

Figure 1. *Vosviewer cluster visualization by co-occurrence. (Mejia, 2025)*



The figure 1 evidence that the main topic is divided in 5 clusters that will be explored in further parts of the document. The identified clusters are the next ones:

- Animal Identification and Tracking
- Health Monitoring and Disease Detection
- Feeding Behavior and Activity Monitoring

- Disease Prediction and Genomic Analysis
- Automation in Meat Production and Processing

Relevance of the Methodology

The use of a Systematic Mapping Study, complemented by VOS Viewer, was crucial for ensuring that this survey captured the most relevant and impactful research in the domain of AI-driven livestock farming. It provided a structured way to explore the literature, preventing the study from being skewed by isolated cases or anecdotal evidence. Instead, the SMS ensured that the documents selected for this review represented a comprehensive overview of the state of the art, while VOS Viewer offered valuable insights into the research landscape by highlighting key areas of focus, collaborations, and trends.

By combining both methodologies, this survey ensured a high level of accuracy and relevance, covering the most significant AI applications in livestock farming and providing a roadmap for future research directions.

Results

Summarizing the results of the search it was obtained the table below.

Table 1. *Summarized research works in the topic (Mejia, 2025)*

Category	Application	Techniques	Reference
Animal Identification & Tracking	Facial recognition of cattle	CNN, DL biometrics	Bergman et al., 2024
Animal Identification & Tracking	Facial recognition of cattle	CNN, DL biometrics	Meng et al., 2023
Animal Identification & Tracking	Pose & skeletal-based recognition	OpenPose, Mask R-CNN	Wang et al., 2023
Animal Identification & Tracking	Robust cattle tracking in occlusion	Multi-feature DL tracking	Mar et al., 2023
Animal Identification & Tracking	Robust cattle tracking in occlusion	Multi-feature DL tracking	Hnin et al., 2024
Animal Identification & Tracking	Traceability in livestock	DL identification	Dac et al., 2022
Animal Identification & Tracking	Traceability in livestock	DL identification	Yukun et al., 2019
Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Ebrahimi et al., 2019
Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Wang et al., 2022
Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Kotlarz et al., 2024
Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Thompson et al., 2023

Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Yesil & Goncu, 2024
Health Monitoring & Disease Detection	Subclinical mastitis detection	GBT, DL, thermal imaging, spectroscopy	Walleser et al., 2023
Health Monitoring & Disease Detection	Lameness detection	Pose estimation, gait CNNs, keypoints	Barney et al., 2023
Health Monitoring & Disease Detection	Lameness detection	Pose estimation, gait CNNs, keypoints	Myint et al., 2024
Health Monitoring & Disease Detection	Lameness detection	Pose estimation, gait CNNs, keypoints	Taghavi et al., 2024
Health Monitoring & Disease Detection	Lameness detection	Pose estimation, gait CNNs, keypoints	Nejati et al., 2023
Health Monitoring & Disease Detection	Calf disease detection	CNN on feeder/video data	Ghaffari et al., 2022
Health Monitoring & Disease Detection	Ocular infections (IBK)	DL classifiers	Gupta et al., 2023
Feeding & Activity Monitoring	Feeding event detection	Computer vision, optimal sampling	Bresolin et al., 2023
Feeding & Activity Monitoring	Daily behavior recognition	CNN + RNN hybrids	Yu et al., 2024
Feeding & Activity Monitoring	Daily behavior recognition	CNN + RNN hybrids	Li et al., 2024
Feeding & Activity Monitoring	Regurgitation monitoring	YOLOv5s + skeletal features	Gao et al., 2023
Genomics & Trait Prediction	Mastitis susceptibility	Explainable DL on WGS	Kotlarz et al., 2024
Genomics & Trait Prediction	Complex trait prediction	deepGBLUP	Lee et al., 2023
Genomics & Trait Prediction	Genomic + behavioral traits	ML on AMS data	Pedrosa et al., 2024
Genomics & Trait Prediction	Enhancer prediction	ML models	MacPhillamy et al., 2022
Genomics & Trait Prediction	Historical genomic review	Genetic selection trends	Weigel et al, 2017
Reproduction & Embryology	Oocyte quality & cumulus expansion	DL quantification	Costa et al., 2023
Reproduction & Embryology	Oocyte quality & cumulus expansion	DL quantification	Raes et al., 2024
Meat Quality & Processing	Carcass marbling grading	MSENet CNN	Lee et al., 2022
Meat Quality & Processing	Freshness detection	Colorimetric sensors + DL	Lin et al., 2024
Meat Quality & Processing	Meat adulteration detection	Spectroscopy + DL	Jo et al., 2023
Meat Quality & Processing	Industrial meat automation	DL robotic limb detection	Manko et al., 2024
Biomedical & Cross-Applications	OCT imaging of lymphatics	DL imaging	Gong et al., 2024
Biomedical & Cross-Applications	Hyperspectral fluorescence imaging	DL + FTIR spectroscopy	Juntunen et al., 2022

Biomedical & Cross-Applications	Remote sensing for schistosomiasis	DL on satellite images	Xue et al, 2023

Applications of Deep Learning in Livestock Farming

Animal identification is a fundamental requirement in livestock production systems because it underpins traceability, health monitoring, genetic evaluation, and management efficiency. Conventional techniques, such as ear tags, branding, or RFID systems, remain widely used; however, they are associated with several limitations. Tags can be lost or damaged, branding raises welfare concerns, and RFID readers may suffer from misreadings, interference, or require close-range scanning ([50]). Furthermore, as herd sizes grow and labor shortages intensify, manual methods become increasingly impractical. This context has motivated the adoption of AI-driven, computer vision–based approaches that allow non-invasive, continuous, and highly accurate animal recognition.

Animal Identification and Tracking

Facial recognition has become one of the most reliable biometric methods due to the relative stability of craniofacial features across an animal's lifetime. [3] introduced a CNN-based recognition framework capable of operating in real time, achieving accuracy levels comparable to human facial ID systems. Meng et al. (2023) addressed the challenge of "known–unknown" classification, where the model must not only recognize animals previously seen during training but also reject unknown individuals with minimal false positives. This contribution is critical for large-scale operations where new animals are frequently introduced, ensuring the robustness of traceability systems.

Figure 2. *Animal identification and tracking presented in Bresolin (2022)*

- *Facial Recognition Systems:* While facial imaging is highly effective, practical challenges arise in barns or pastures where camera positioning, animal crowding, or environmental conditions may obscure the face. To address this, Wang et al. (2023) proposed a Mask R-CNN coupled with OpenPose for cattle identification based on skeletal landmarks, such as the spine, legs, and head position. This method expands the applicability of biometric recognition by enabling identification even when the animal's head is not visible. By leveraging skeletal geometry, pose-based identification also provides ancillary data for behavior and welfare monitoring.

- *Pose and Skeleton-Based Identification:* While facial imaging is highly effective, practical challenges arise in barns or pastures where camera positioning, animal crowding, or environmental conditions may obscure the face. To address this, Wang et al. (2023) proposed a Mask R-CNN coupled with OpenPose for cattle identification based on skeletal landmarks, such as the spine, legs, and head position. This method expands the applicability of biometric recognition by enabling identification even when the animal's head is not visible. By leveraging skeletal geometry, pose-based identification also provides ancillary data for behavior and welfare monitoring.

- *Automated Traceability and Integration with Precision Farming:* Traceability is not merely a technical challenge but also a regulatory and market demand. Consumers increasingly expect transparency in food production, while governments enforce traceability for disease control and export certification. AI-based biometric identification supports these goals by providing tamper-proof recognition [6]; [50]). When integrated with herd management platforms, these systems can automatically link an animal's identity to health records, genetic information, feeding patterns, and production metrics, forming the backbone of precision livestock farming.

- *Multi-Feature Tracking Under Occlusion:* Another frontier in animal identification involves robust tracking under occlusion. Farm environments are inherently dynamic: animals often overlap, obstruct each other, or move between shadows and direct sunlight. Mar et al. (2023) and Hnin et al. (2024) developed multi-feature tracking algorithms that combine visual descriptors (color, shape, movement) with DL models to maintain individual recognition even in crowded pens. These systems demonstrate resilience to partial visibility and confirm the feasibility of continuous monitoring in group-housed conditions, where traditional single-animal methods fail.

- *Pose and Behavior-based Identification:* an additional approach to cattle identification is through pose estimation. Wang et al. (2023) introduced an OpenPose Mask R-CNN model to recognize individual cattle by analyzing their skeletal structure and body movements. By capturing and interpreting the body poses, the system can uniquely identify animals even when the face is not visible. This technique is particularly beneficial in cases where face-based systems may fail due to occlusion or poor image quality.

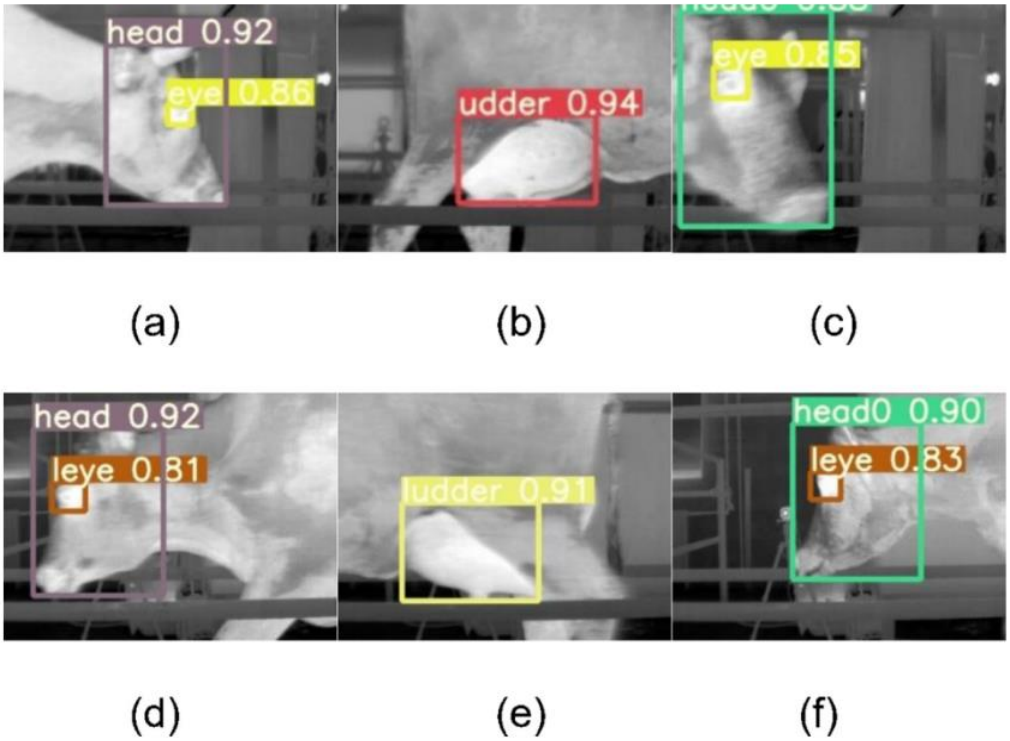
Overall, the transition from manual identification methods toward AI-driven biometric recognition marks a paradigm shift in livestock management. Facial and pose-based recognition systems achieve accuracies above 95%, outperforming RFID in robustness to environmental variability. Multi-feature tracking enables monitoring in realistic, crowded farm environments, addressing one of the key barriers to practical adoption. Furthermore, integration with traceability frameworks enhances compliance, food safety, and consumer trust.

Nevertheless, challenges remain, including the need for large annotated datasets to train recognition models, domain adaptation across different breeds and environments, and ensuring cost-effective implementation in diverse farming systems. Future directions in this cluster will likely emphasize multimodal fusion—combining facial, skeletal, and gait features—to achieve near-perfect recognition with minimal computational overhead.

Health Monitoring and Disease Detection

Maintaining livestock health is a key factor in ensuring high productivity and animal welfare. Deep learning has played a transformative role in automating health monitoring and early disease detection through advanced image processing and sensor data analysis.

Figure 3. *Mastitis detection presented by Y. Wang (2022)*



- *Mastitis Detection:* mastitis is a common and economically significant disease in dairy cows, often leading to reduced milk yield and quality. Wang et al. (2022) used infrared thermal imaging and deep learning models to detect mastitis in cows with high accuracy. By analyzing thermal images of the cows' udders, the model identified temperature anomalies indicative of inflammation, which is a primary symptom of mastitis. This non-invasive detection method offers a significant advantage over traditional clinical methods, which are typically labor-intensive and time-consuming.

- *Lameness Detection:* lameness is another critical health issue in dairy farming, affecting the mobility and overall well-being of cows. Early detection of lameness allows for timely interventions, reducing the risk of long-term mobility issues. Barney et al. (2023) utilized deep learning techniques, specifically pose estimation algorithms, to detect lameness in multiple cows simultaneously. Their approach involved the use of CNNs to analyze the gait and posture of cows, identifying subtle changes that may indicate lameness. This automated detection system significantly reduces the time required for manual inspections, improving the overall efficiency of health monitoring in dairy herds.

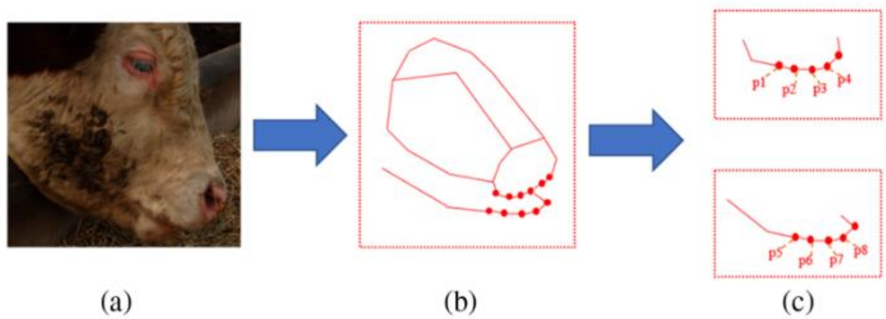
- *Disease Monitoring in Calves:* health monitoring systems for younger livestock, such as pre weaning calves, have also benefited from deep learning advancements. Ghaffari et al. (2022) developed a deep CNN-based system for detecting diseases like diarrhea and respiratory infections in calves. The system analyzed images and videos of the calves, identifying symptoms such as abnormal posture and lethargy. By automating the detection process, farmers can intervene earlier, reducing the impact of diseases on calf mortality and growth rates.

Deep learning-based health monitoring systems are reshaping the way diseases are detected in livestock, offering real-time, accurate, and non-invasive solutions that enhance animal welfare and farm productivity.

Feeding Behavior and Activity Monitoring

Monitoring feeding behavior is critical in dairy farming, as it directly influences milk production and animal health. AI-driven systems powered by deep learning are helping farmers optimize feeding strategies by providing detailed insights into animal behavior.

Figure 4. *Cattle skeleton key point representation diagram presented by Guohong Gao (2023)*



- *Image Acquisition for Feeding Behavior:* [4] investigated the optimal image acquisition frequency required to monitor feeding behavior in Holstein heifers using computer vision systems. They determined that image sampling rates need to balance data efficiency with monitoring accuracy. By adjusting the frequency of image captures, the system effectively tracked feeding events and behaviors, ensuring precise measurements of feed intake without overwhelming data storage systems.

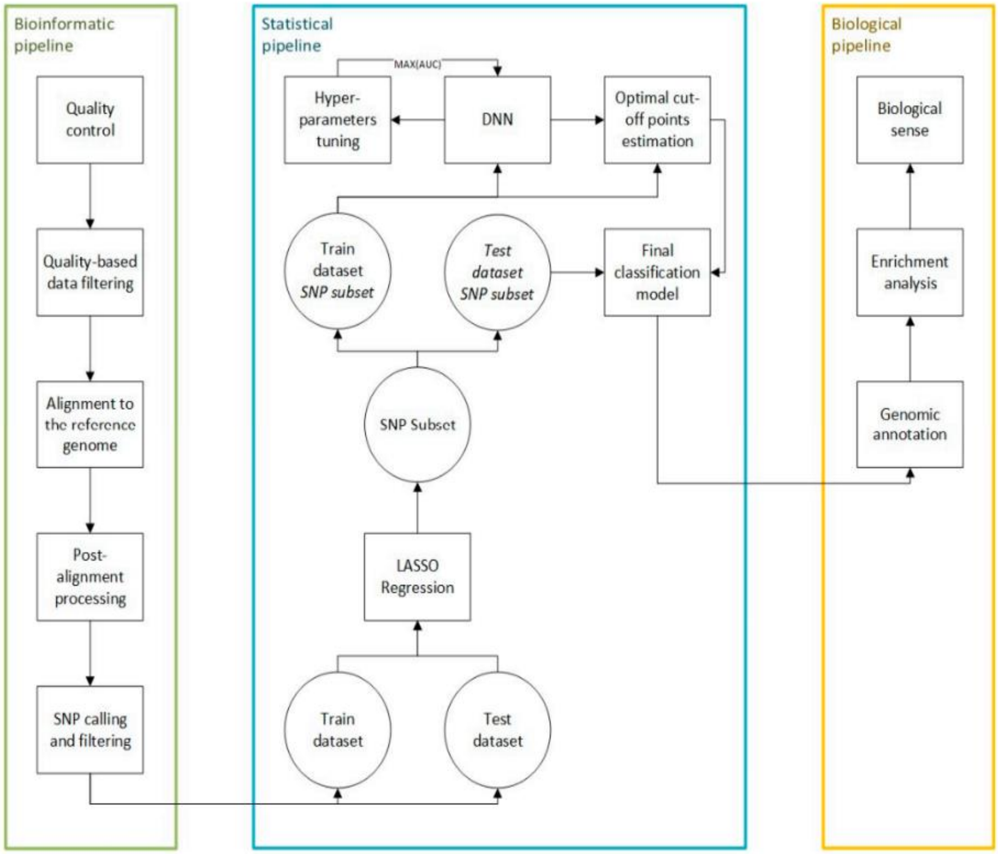
- *Behavior Recognition through Deep Learning:* understanding animal behavior, particularly feeding and movement patterns, is essential for identifying signs of stress, disease, or undernutrition. Yu et al. (2024) and Luo et al. (2024) developed deep learning-based systems to recognize daily behaviors in dairy cows. These systems employed CNNs and recurrent neural networks (RNNs) to analyze video feeds, identifying specific actions such as grazing, walking, lying down, and eating. Automated behavior recognition allows farmers to detect anomalies in real-time, enabling prompt interventions if cows exhibit signs of illness or stress. Furthermore, such systems can optimize feeding schedules by identifying peak feeding times and minimizing wastage.

AI-driven feeding behavior analysis improves resource utilization and ensures that cows receive appropriate nutrition, leading to higher milk yields and healthier herds.

Disease Prediction and Genomic Analysis

Beyond physical and behavioral monitoring, deep learning has made strides in predicting diseases based on genomic data. By leveraging large-scale genomic datasets, AI models can identify animals at risk of developing specific diseases, improving breeding programs and disease management.

Figure 5. *Flow diagram of data analysis for genome Kotlarz (2024)*



● *Mastitis Prediction through Genomics:* Kotlarz et al. (2024) developed a deep learning classifier that predicts bovine mastitis by analyzing whole-genome sequence data. The model used explainable AI techniques to identify key genetic markers associated with mastitis susceptibility. This approach enables farmers to make informed decisions about breeding and herd management, potentially reducing the prevalence of mastitis in future generations.

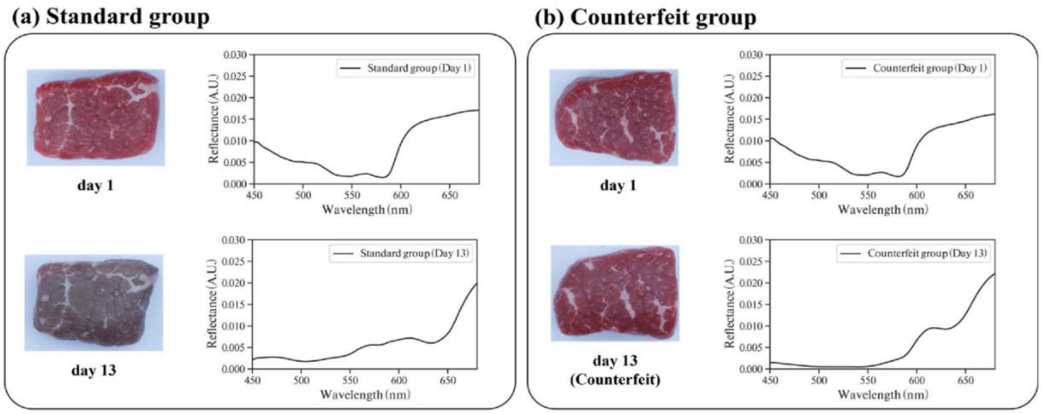
● *Genomic Prediction of Complex Traits:* genomic prediction models are invaluable for selecting livestock with desirable traits, such as high milk production or disease resistance. Lee et al. (2023) introduced deepGBLUP, a framework that integrates deep learning with genomic best linear unbiased prediction (GBLUP) to predict complex traits in Korean native cattle. By combining the strengths of deep learning with traditional genomic prediction methods, deepGBLUP provided more accurate and reliable predictions of genetic traits. This advancement holds promise for enhancing selective breeding programs and improving overall herd productivity.

Deep learning applications in genomic analysis are paving the way for more precise and efficient breeding strategies, with the potential to reduce the incidence of genetic diseases and improve livestock performance.

Automation in Meat Production and Processing

Deep learning is also transforming the meat production industry by automating processes such as carcass grading, quality assessment, and meat handling. These innovations not only improve efficiency but also enhance product quality and consistency.

Figure 6. *Comparison of surface images and spectral information of randomly selected beef samples from the standard and counterfeit groups on day 1 and day 13 Eunjung (2023)*



● *Automated Carcass Grading:* Lee et al. (2022) developed the MSENet (Marbling Score Estimation Network), a deep learning-based system for automatically grading beef carcasses. The system analyzed high-resolution images of beef cuts, estimating marbling scores with a high degree of accuracy. By automating the grading process, MSENet reduces the subjectivity and variability of manual grading methods, ensuring consistent product quality.

● *Meat Factory Automation:* in the context of meat processing, automation is essential for enhancing productivity and reducing labor costs. Manko et al. (2024) created a deep learning system that automates the detection and gripping of limbs in meat processing factories. The system uses object detection algorithms to identify and manipulate meat products with precision, increasing the speed and accuracy of meat handling in industrial settings

Table 2. *Application of Deep Learning in Livestock Farming (Mejia, 2025)*

Application of Deep Learning in Livestock Farming		
Application	**Example**	**Technique**
Animal Identification and Tracking	Facial Recognition Systems	Convolutional Neural networks (CNN's) to extract unique features from the cows' faces
	Pose and Behavior-based Identificaction	Open Pose Mask R-CNN to recognize individual cattle by analyzing their skeletal structure and body movements
Health Monitoring and Disease Detection	Mastitis Detection	Infrared thermal imaging and deep learning models
	Lameness Detection	CNN's to analyze the gait and posture of cows
	Disease Monitoring in Calves	Deep CNN-based system for detecting diseases like diarrhea and respiratory infections in calves

Feeding Behavior and Activity Monitoring	Image Acquisition for Feeding Behavior	Computer vision systems to monitor eating behavior
	Behavior Recognition through Deep Learning	Employed CNNs and recurrent neural networks (RNNs) to analyze video feeds, identifying specific actions such as grazing, walking, lying down, and eating
Disease Prediction and Genomic Analysis	Mastitis Prediction through Genomics	Deep learning classifier that predicts bovine mastitis by analyzing whole-genome sequence data
	Genomic Prediction of Complex Traits	introduced deepGBLUP, a framework that integrates deep learning with genomic best linear unbiased prediction (GBLUP) to predict complex traits in Korean native cattle
Automation in Meat Production and Processing	Automated Carcass Grading	MSENet (Marbling Score Estimation Network), a deep learning-based system for automatically grading beef carcasses
	Meat Factory Automation	created a deep learning system that automates the detection and gripping of limbs in meat processing factories

Challenges and Future Directions

Despite the significant advancements in using AI and deep learning technologies in livestock farming, several challenges remain. These challenges span from technological limitations and data constraints to ethical concerns and the need for interdisciplinary collaboration. This section outlines the key challenges faced in implementing these technologies and proposes future directions to overcome them.

Data Quality, Availability, and Integration

One of the primary challenges in deploying AI solutions in livestock farming is the quality and availability of data. Although deep learning models have proven to be highly effective, their performance depends on the quantity and quality of the data used for training. In many cases, the data collected from livestock farms are sparse, noisy, and fragmented, leading to difficulties in model generalization and real-world applicability.

For example, studies like [4] emphasize the need to optimize the frequency of image acquisition in computer vision systems to monitor feeding behavior, suggesting that a delicate balance must be struck between the quality and frequency of data collection. Similarly, studies like Ferreira, Lee, and Dórea (2023) advocate for the use of pseudo-labeling techniques to improve the performance of animal identification models, which highlights the importance of maximizing the utility of available data.

Another challenge relates to data integration. Modern farms often employ a variety of sensors, cameras, and monitoring systems, all of which produce large volumes of heterogeneous data. Integrating these data streams in a cohesive manner can be difficult, especially when data standards are lacking. As noted by Luo et al. (2024), precision tracking systems require high levels of accuracy in positioning data to effectively monitor animal behavior, underscoring the complexity of managing large, real-time data streams.

Model Generalization and Scalability

The scalability of AI models across different farm environments presents another significant challenge. Deep learning models trained in one farm setting may not generalize well to another, due to differences in environmental conditions, animal breeds, and management practices. This is particularly true in applications such as disease detection and behavior recognition, where models trained on specific farms may not perform well when transferred to farms with different conditions. Studies like Wang et al. (2023), which explore pose estimation for individual cattle recognition, emphasize the difficulties in ensuring model generalization across multiple farm environments.

This lack of generalizability is partly due to the complexity and variability of animal behavior. For instance, detecting mastitis using thermal images, as shown by Wang et al. (2022), may require different calibration across various breeds and environmental settings. Furthermore, differences in the quality of infrastructure and sensors across farms can also impact the performance of AI systems, as discussed by Pedrosa et al. (2024).

Ethical Considerations and Animal Welfare

The integration of artificial intelligence into livestock management and biomedical research raises profound ethical questions that extend beyond the technical performance of models. While ML and DL approaches offer unprecedented opportunities for efficiency, precision, and animal welfare improvements, they also introduce risks related to over-surveillance, data governance, equity, and societal acceptance. These concerns demand careful evaluation to ensure that technological innovation is aligned with ethical principles and long-term sustainability.

Animal Welfare and Over-Monitoring

A central ethical issue lies in balancing the benefits of AI-based monitoring with the potential for excessive control over animals. Computer vision systems now allow the continuous surveillance of individual cows, pigs, and other livestock, tracking behaviors such as feeding, lying, walking, and even regurgitation (Yu et al., 2024; [11]). While such monitoring can detect diseases earlier and prevent suffering, the possibility of constant surveillance may raise concerns about animals being reduced to data points, with little consideration for their intrinsic value as sentient beings. Ethical livestock management requires that technological tools be applied to enhance welfare—by enabling earlier interventions and reducing invasive diagnostic practices—rather than simply maximizing production efficiency.

Data Privacy and Ownership

The proliferation of sensors, cameras, and automated systems in farms and laboratories generates vast amounts of behavioral, genetic, and health-related data. Unlike human healthcare, where strict regulations such as GDPR govern data ownership and privacy, livestock data remain in a regulatory gray zone. Questions arise regarding who owns genomic information from herds (farmers, breeding companies, or technology providers), and how such data should be shared, monetized, or protected. Commercial platforms that integrate AI-driven precision farming may establish monopolies by controlling access to data, creating ethical and economic imbalances that disadvantage smaller farmers. Transparent frameworks for data governance, with fair benefit-sharing mechanisms, are urgently required.

Bias, Equity, and Model Generalization

Another ethical dimension relates to **bias** in AI models. Most datasets for cattle identification, mastitis prediction, or lameness detection are collected in high-income countries under controlled farm conditions [9]; [2]. Models trained in these contexts may fail to generalize to smallholder or extensive farming systems common in low- and middle-income regions. This creates a technological inequity, where cutting-edge AI systems may be inaccessible or ineffective in contexts that could benefit from them most. Addressing this bias requires deliberate efforts to include diverse environments, breeds, and management systems in training datasets, ensuring that AI benefits are equitably distributed across global agriculture.

Transparency and Explainability

Ethical AI requires transparency in how predictions and decisions are made. In health-critical tasks such as mastitis detection or genomic selection, black-box DL models may produce highly accurate predictions but offer little insight into the features or mechanisms underlying their outputs. Without explainability, veterinarians and farmers may struggle to trust or act on AI recommendations, and responsibility in case of errors remains ambiguous. Efforts toward interpretable and explainable AI ([19]) represent not only a technical priority but also an ethical imperative, ensuring accountability and informed decision-making in animal health and breeding.

Reduction of Antibiotic Use vs. Over-Industrialization

One of the strongest ethical justifications for AI in livestock farming is its potential to reduce reliance on antibiotics by enabling earlier and more precise disease detection ([40]; [12]). However, there is also a counter-risk: that AI could reinforce industrialized production models that prioritize efficiency and high stocking densities, potentially exacerbating the very welfare and environmental challenges that precision livestock farming seeks to address. Ensuring that AI is deployed to support *One Health* principles—balancing animal welfare, human health, and environmental stewardship—should guide the ethical framework for implementation.

Economic and Social Dimensions

The adoption of AI in farming may widen gaps between large, technologically advanced farms and smallholders with limited resources. Advanced systems such as deepGBLUP ([21]) or multi-camera lameness detection require infrastructure investments beyond the reach of many small-scale farmers. If unregulated, this may accelerate consolidation in the livestock industry, marginalizing smallholders and reducing rural employment. Ethically responsible innovation should therefore prioritize affordability, modularity, and training programs that enable inclusive adoption across scales of production.

Conclusion of Ethical Considerations

In summary, the ethical implications of AI in livestock and biomedical research revolve around balancing innovation with fairness, transparency, and sustainability. To ensure ethical alignment, future research must emphasize: (i) the enhancement of animal welfare rather than pure productivity gains; (ii) transparent and inclusive data governance frameworks; (iii) mitigation of bias and promotion of equity across diverse farming systems; and (iv) development of explainable, accountable AI systems that reinforce trust. Interdisciplinary collaboration between veterinarians, ethicists, engineers, and policymakers is essential to transform AI from a purely technical advancement into a socially and ethically responsible innovation.

Costs and Access to Technology

The adoption of AI-based solutions in livestock and biomedical research is shaped not only by technical performance but also by **economic feasibility and accessibility**. While DL and ML models have demonstrated superior accuracy in tasks such as mastitis detection [9]; [42]), lameness monitoring [2]; [29]), and genomic prediction ([21]; [19]), their practical deployment requires hardware, software, and infrastructure investments that are not equally accessible to all producers. This raises significant concerns about cost distribution, scalability, and the risk of excluding small and medium-sized farmers from the benefits of technological innovation.

Infrastructure and Hardware Costs

Modern AI applications frequently depend on high-resolution imaging systems, thermal cameras, RGB-D sensors, or advanced milking systems integrated with sensors ([30]). These devices, while essential for data acquisition, represent considerable upfront investments. For example, lameness detection using side-view cameras ([29]) or pose-estimation systems ([37]) requires multi-camera setups, network connectivity, and reliable storage for large video datasets. Similarly, genomic prediction methods such as deepGBLUP ([21]) require access to sequencing technologies and bioinformatics pipelines, which are financially prohibitive for many small-scale producers.

Maintenance and Operational Expenses

The true cost of AI extends beyond hardware acquisition. Maintenance of sensors, calibration of cameras, and continuous software updates are necessary to sustain accuracy over time. Cloud-based platforms, increasingly used for AI analytics, introduce recurring subscription costs and require stable internet connections, which may not be available in remote or rural areas. Moreover, the need for skilled personnel to manage and interpret AI systems adds indirect labor costs, limiting adoption in settings where technical training is scarce.

Disparities in Access Between Large and Small Farms

Large-scale industrial farms are more likely to adopt AI technologies, benefiting from economies of scale that justify high capital expenditures. In contrast, smallholders, particularly in low- and middle-income countries, face structural barriers to adoption ([33]). This imbalance risks widening the productivity and profitability gap between farm types, contributing to rural economic inequality. While AI could theoretically democratize precision farming, in practice, unequal access to technology may reinforce consolidation trends in the livestock industry, marginalizing small producers.

Cost-Benefit Analysis and Return on Investment

An essential question for adoption is whether AI solutions provide a clear economic return on investment (ROI). For example, early mastitis detection through AI reduces veterinary expenses and productivity losses, potentially offsetting hardware costs within a few years [9]; [40]). Similarly, genomic prediction tools improve breeding efficiency, increasing long-term profitability ([19]). However, these benefits often materialize only in large herds or under high-input systems. For smaller farms, the ROI may be less compelling, especially when costs of adoption compete with other urgent resource needs.

Open-Source Tools and Low-Cost Alternatives

Encouragingly, recent efforts explore **open-source frameworks** and low-cost sensors to reduce economic barriers. For example, [4] demonstrated that optimizing the frequency of image acquisition reduces storage and computational costs without sacrificing performance in feeding behavior monitoring. Likewise, lightweight CNNs such as YOLOv5n ([11]) and transfer learning approaches can run on low-power devices, making them more accessible. Such innovations highlight the importance of tailoring AI solutions to diverse contexts, ensuring that small-scale farmers also benefit.

Policy and Financial Incentives

Governments and international organizations can play a critical role in addressing cost-related barriers. Subsidies for sensor acquisition, cooperative data-sharing platforms, and training programs may democratize access to AI tools, ensuring broader participation. Without such interventions, AI adoption may remain concentrated in advanced industrial farms, undermining its potential as a tool for sustainable and inclusive agriculture.

Conclusion of Costs and Access

In summary, while AI in livestock and biomedical applications offers significant economic potential, the **high costs of infrastructure, recurring maintenance expenses, and disparities in access** present major obstacles. To avoid deepening inequalities in the agricultural sector, future development must prioritize affordability, modularity, and open-source innovation. Policies promoting subsidies, cooperative ownership models, and capacity building are necessary to ensure that AI contributes to **inclusive technological progress**, rather than reinforcing existing divides between large-scale operations and smallholder farmers.

Future Directions

Although machine learning and deep learning have already demonstrated significant impact in livestock and biomedical research, the field remains dynamic, with substantial opportunities for innovation. Future work will likely concentrate on multimodal integration, scalability, explainability, ethical alignment, and translational synergies between agriculture and medicine. These directions represent not only technical challenges but also the broader agenda of designing AI systems that are transparent, equitable, and welfare-oriented.

1. Multimodal and Sensor Fusion Approaches

Current applications frequently rely on a single type of data, such as RGB imagery for animal identification [4]; [28]), infrared thermography for mastitis detection ([42]), or genomic datasets for trait prediction ([21]). However, no single modality can fully capture the complexity of livestock physiology and behavior. Future research should integrate multimodal data streams—including video, thermal imaging, accelerometer signals, genomic data, and feeding records—into unified frameworks. Sensor fusion has the potential to increase robustness, reduce false positives, and enable a holistic understanding of animal health and productivity.

2. Domain Adaptation and Generalization

A recurring limitation of current AI systems is their dependency on farm-specific datasets. Models trained in intensive, high-income farming systems may fail when applied to smallholder contexts with different breeds, housing, or feeding regimes ([33]; [30]). Future research should emphasize domain adaptation techniques, including transfer learning, federated learning, and unsupervised domain alignment, to ensure that models generalize across heterogeneous environments. Developing benchmarks that include datasets from diverse geographic regions and production systems will also be critical to achieving global relevance.

3. Explainable and Trustworthy AI

The ethical imperative of transparency will drive a stronger emphasis on explainable AI (XAI). In high-stakes applications such as mastitis prediction ([19]) or genomic selection ([45]), farmers and veterinarians must understand why a model makes a specific recommendation. Future systems will therefore integrate visualization tools, attention mechanisms, and post-hoc explainers to increase interpretability. Beyond technical transparency, embedding accountability frameworks will reinforce trust and ensure that AI systems support evidence-based decision-making rather than operating as opaque black boxes.

4. Cost Reduction and Inclusive Access

Future research must also prioritize scalable and affordable solutions. Lightweight architectures (e.g., YOLOv5n, [11]) and optimized image sampling strategies [4] demonstrate that high performance can be achieved without expensive hardware. Expanding these efforts will be critical for democratizing access in low- and middle-income countries. Collaborations with policymakers and cooperatives should focus on subsidized infrastructure, open-source platforms, and cooperative data sharing, ensuring that AI adoption benefits both large-scale operations and smallholders.

5. Cross-Sectoral Integration: One Health Perspective

The convergence of livestock research with biomedical science is expected to intensify. Advances in oocyte assessment ([34]; [5], lameness detection [2], and disease surveillance ([47]) illustrate how agricultural AI pipelines can inform medical imaging, reproductive medicine, and public health monitoring. Conversely, biomedical advances in imaging ([14]; [18]) and genomics can be adapted for livestock contexts. Future research agendas should embrace the One Health framework, promoting interdisciplinary collaboration to address animal welfare, human health, and environmental sustainability simultaneously.

6. Ethical and Social Embedding

Building on the ethical considerations previously discussed, future AI applications must integrate ethical impact assessments during the design phase. This includes analyzing potential effects on animal welfare, equity among farmers, data ownership, and societal perceptions of surveillance technologies. Developing international guidelines for ethical AI in agriculture, similar to those emerging in human medicine, will help establish trust and legitimacy.

Conclusions

Artificial intelligence, and particularly the integration of machine learning (ML) and deep learning (DL) methods, has initiated a paradigm shift in livestock production and biomedical research. The evidence synthesized in this review demonstrates that AI-driven approaches surpass traditional statistical and manual methods in nearly every major area of application—ranging from early detection of mastitis ([9]; [42]; [19]) and lameness ([2]; [29]), to behavioral monitoring ([4]; Yu et al., 2024), reproductive assessment ([34]; [5]), genomic prediction ([21]; [33]), and automation in meat quality evaluation ([20]; [23]). These advances illustrate the transformative potential of AI not only to improve efficiency and productivity, but also to enhance **animal welfare, food safety, and sustainability**.

From a practical standpoint, the studies reviewed converge on several key strengths of AI in livestock and biomedical systems. First, AI-based systems consistently reduce the subjectivity and variability inherent in human evaluation, offering reproducible and objective assessments across diverse environments. Second, they facilitate **non-invasive monitoring**, reducing animal stress compared to traditional diagnostic methods. Third, AI creates opportunities for **continuous, real-time surveillance** of large herds, something unattainable with manual observation. Finally, by integrating genomic, behavioral, and imaging data, AI paves the way for **holistic decision-making frameworks** that connect health, productivity, and welfare at both the individual and herd levels.

At the same time, the findings also expose the limitations and challenges that define the current frontier. **Data heterogeneity and quality** remain a major bottleneck. Models trained on high-income, intensive farming datasets often fail when transferred to smallholder or extensive production systems ([30]; [33]). This creates inequities in technological benefit, where large-scale farms capitalize on AI, while small producers are left behind. Furthermore, the **cost of hardware, infrastructure, and maintenance** represents a barrier to widespread adoption ([29]; [2]). Without deliberate cost-reduction strategies, AI may accelerate consolidation in the livestock industry, deepening economic divides.

Equally pressing are the **ethical considerations** raised by AI adoption. Constant surveillance of animals, while valuable for disease prevention, raises concerns about reducing sentient beings to data points. Questions of **data ownership and privacy** remain unresolved in livestock contexts, and the concentration of genomic and behavioral datasets in private corporations risks creating monopolies that marginalize farmers ([32]; [36]). Additionally, the reliance on black-box DL systems undermines trust when predictions cannot be explained or validated by human expertise ([19]). Addressing these issues requires a shift toward **explainable AI** and transparent governance frameworks.

Looking toward the future, the next decade of research and development must emphasize several strategic directions. **Multimodal fusion**, combining visual, thermal, genomic, and sensor-derived data streams, will allow for richer, more robust predictions. **Domain adaptation and transfer learning** are essential to ensure that models trained in one environment can generalize across breeds, climates, and production systems. **Lightweight, low-cost AI solutions** running on edge devices will democratize access, particularly in low- and middle-income countries. Moreover, embedding AI within a **One Health framework**—linking animal welfare, human health, and environmental sustainability—will maximize societal impact. The cross-pollination between biomedical imaging ([14]; [18]) and livestock monitoring ([34]; [11]) illustrates the potential of interdisciplinary collaboration to accelerate innovation.

In conclusion, AI in livestock and biomedical research stands at a crossroads. On one side, it offers the promise of **sustainable intensification**, where efficiency gains coincide with improved welfare and reduced environmental impact. On the other, without careful attention to ethics, costs, and inclusivity, it risks reinforcing inequities and prioritizing productivity over welfare. The challenge for researchers, policymakers, and practitioners is to ensure that AI evolves not only as a tool of efficiency but as a **responsible, transparent, and globally inclusive innovation**. If this vision is realized, AI can become a transformative force that simultaneously advances animal welfare, ensures food security, protects public health, and supports the transition toward more ethical and sustainable agricultural systems worldwide.

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