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Review of Integration of Artifical Intelligence and Iot in Precision Livestock Farming

Novantyo,M.F., Rahmawati,O., Makkah,K, Dynata, A.R, Busa, F.T.B., Wijoyo,I.A, Nurdianti
Politeknik Pembangunan Pertanian Malang

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Corresponding Author:
faizalnovan86@gmail.com

Abstract
Traditional livestock management faces growing challenges in efficiency, animal welfare, and environmental sustainability. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies offers transformative opportunities for precision livestock farming through real-time monitoring, predictive analytics, and automated decision-making. This systematic review, using the PRISMA methodology, analyzed 62 peer- reviewed studies published between 2023 and 2025 across four domains: (1) AI-based disease detection and health monitoring, (2) IoT-driven feeding and nutrition management, (3) reproductive and behavioral monitoring, and (4) integrated AI–IoT farm management systems. Results show that machine learning models achieve 85– 95% accuracy in early disease detection, while IoT sensor networks reduce feed waste by 20–35% through optimized distribution. Smart platforms also improve reproductive efficiency by 15–25% and lower mortality rates by 12–18% in various livestock species. Despite these benefits, challenges remain in terms of high investment costs, data security, system interoperability, and limited farmer technical capacity. Smallholders are particularly affected by these barriers. Future research should prioritize low-cost sensor innovations, strong data governance frameworks, and user-friendly interfaces. Overcoming these obstacles is crucial to make precision livestock technologies accessible, equitable, and sustainable, enhancing productivity while safeguarding animal welfare and the environment.

INTRODUCTION

In recent decades, the global demand for animal-based products such as meat, milk, and eggs has increased significantly, driven by population growth and changes in dietary patterns. However, conventional livestock management systems that rely heavily on manual observation, farmer intuition, and experiential knowledge face increasing challenges in meeting modern standards of productivity, sustainability, and animal welfare. The lack of real-time monitoring often delays the detection of diseases, stress, or nutritional imbalances, leading to reduced productivity and economic losses. Moreover, inefficient use of resources such as uneven feed distribution and excessive water consumption exacerbates both economic and environmental pressures. At the same time, growing public awareness of animal welfare and environmental sustainability has intensified the call for smarter, data-driven livestock management systems (Berckmans, 2024; Wathes et al., 2023).

To address these challenges, the concept of Precision Livestock Farming (PLF) has emerged as an innovative approach that leverages Artificial Intelligence (AI) and the Internet of Things (IoT) to enhance decision-making in livestock operations. PLF enables the continuous individual monitoring of animals through environmental sensors, cameras, and wearable devices that collect physiological, behavioral, and performance data. IoT technologies support real-time data transmission and integration, while AI and machine learning algorithms analyze large datasets to detect anomalies, predict events, and optimize farm management (Nyamuryekung'e et al., 2024; Liu et al., 2023). PLF applications are no longer limited to intensive systems but have also expanded to extensive settings, known as Precision Livestock Extensive Farming (PLEF), which involves pasture management, animal tracking, and adaptive monitoring in open-field environments (Tzanidakis et al., 2023). Studies have demonstrated that such systems can significantly enhance productivity, reduce mortality rates, and improve animal welfare through early disease detection and optimized feeding strategies (Zhang et al., 2024; Sun et al., 2023).

Empirical research has further highlighted the tangible benefits of AI IoT integration in livestock systems. Gao et al. (2024) and Martínez-Fernández et al. (2023) reported that machine learning algorithms in PLF applications achieved 85–95% accuracy in disease detection, while IoT sensor networks reduced feed waste by 20–35% through optimized distribution. Smart monitoring platforms have also been shown to improve reproductive efficiency by 15–25% and decrease mortality rates by 12–18% across various livestock species. Furthermore, recent developments in digital twin technology have introduced virtual representations of livestock systems that are synchronized with real-time data, allowing simulation and prediction of environmental conditions, animal health, and management outcomes (MDPI, 2024). In cattle systems, for instance, digital twins can model animal responses to environmental variations and management interventions, providing decision support for sustainable production planning.

Beyond productivity, AI and IoT technologies also play a crucial role in improving animal welfare. A human-centric approach emphasizes that these technologies are not intended to replace farmers but to empower them by providing objective, real-time information on animal behavior and physiological status (Springer, 2023). However, despite their potential, several barriers hinder the widespread adoption of PLF technologies. High initial investment costs remain a major challenge, especially for small and medium-scale farmers in developing regions. Other critical issues include data security and privacy, the lack of interoperability standards among devices, and limited technical capacity and digital literacy among farmers (Kumar et al., 2024; *Frontiers in Veterinary Science*, 2023).

The digital divide between technologically advanced commercial farms and resource-limited smallholders poses a growing risk of inequality in productivity and animal welfare outcomes (FAO, 2024; Lee et al., 2025). Many IoT-based livestock systems still rely on local data storage without cloud integration and offer limited user interfaces, reducing accessibility and data utility (MDPI, 2024). Therefore, the implementation of PLF should not only focus on technological innovation but also consider social, economic, and accessibility aspects to ensure inclusive adoption across different production scales.

Given these dynamics, this study aims to conduct a systematic review of recent developments in AI and IoT applications in livestock systems between 2023 and 2025 using the PRISMA methodology. The review focuses on identifying empirical outcomes of technology adoption such as improvements in production efficiency, reproduction, and animal health while also exploring key barriers to implementation. Furthermore, it outlines future research directions, including the development of low-cost sensor technologies, comprehensive data governance frameworks, and user-friendly interface designs. Ultimately, this review seeks to contribute to the democratization of precision livestock technologies by promoting sustainable, inclusive, and scalable livestock production systems that enhance productivity, ensure animal welfare, and support environmental stewardship.

RESEARCH METHODOLOGY

Research Design and Protocol

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological rigor, transparency, and reproducibility. The objective was to synthesize recent empirical findings on the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in livestock production systems, covering publications from January 2023 to June 2025. The review protocol was registered prospectively to minimize reporting bias and ensure adherence to predefined selection criteria (Moher et al., 2015).

Database Selection

A comprehensive literature search was carried out using the Scopus database, selected for its extensive coverage of peer-reviewed journals in agriculture, engineering, veterinary science, and computer science (Gusenbauer & Haddaway, 2020). Scopus was chosen due to its superior indexing of multidisciplinary research and consistent metadata quality compared to other databases (Pranckutė, 2021). Additional relevant studies were identified through manual screening of reference lists from previously selected papers and forward citation tracking using Google Scholar.

Search Terms and Boolean Operators

(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Neural Network” OR “Computer Vision” OR “Convolutional Neural Network” OR “Random Forest” OR “Support Vector Machine” OR “YOLO” OR “CNN”)

The search strategy employed Boolean operators and combinations of keywords related to precision livestock farming, AI, and IoT applications. The comprehensive search string included:

(“Internet of Things” OR “IoT” OR “sensor network” OR “wireless sensor” OR “smart device” OR “wearable sensor” OR “RFID” OR “GPS tracking” OR “environmental sensor”)
AND
(“livestock” OR “cattle” OR “dairy” OR “beef” OR “poultry” OR “swine” OR “pig” OR “sheep” OR “goat” OR “broiler” OR “layer” OR “animal farming” OR “precision livestock farming” OR “PLF”)
AND
(“health monitoring” OR “disease detection” OR “reproduction” OR “estrus detection” OR “feeding” OR “nutrition” OR “behavior” OR “welfare” OR “productivity” OR “efficiency” OR “mortality” OR “weight gain”)

Filters were applied to restrict results to peer-reviewed journal articles in English, published between January 2023 and June 2025, with full-text availability.

Eligibility Criteria

Eligibility criteria were established prior to the review. A study was considered eligible if it empirically implemented both AI and IoT technologies within livestock production systems and reported quantitative outcomes related to productivity, efficiency, reproduction, disease detection, animal welfare, or resource optimization. Only peer-reviewed English- language journal articles published between 2023 and 2025 were included. Studies were excluded if they focused solely on either AI or IoT, lacked empirical data, were published outside the specified timeframe, or addressed non-livestock species.

Inclusion Criteria

- Empirically implemented both AI and IoT technologies within livestock production systems
- Reported quantitative outcomes related to productivity, efficiency, reproduction, disease detection, animal welfare, or resource optimization
- Published in peer-reviewed English-language journals between 2023 and 2025
- Provided sufficient methodological detail to assess quality and reproducibility
- Focused on terrestrial livestock species (cattle, swine, poultry, sheep, goat

Exclusion Criteria

- Focused solely on either AI or IoT (not integrated systems)
- Lacked empirical data (e.g., review papers, theoretical models, opinion pieces)
- Were published outside the specified timeframe
- Addressed non-livestock species (aquaculture, companion animals, wildlife)
- Were non-peer-reviewed materials (conference abstracts, theses, grey literature)
- Provided insufficient data for quality assessment

The selection and analysis processes strictly followed the PRISMA flow protocol. All retrieved records were exported into reference management software to remove duplicates. Two independent reviewers screened titles and abstracts according to inclusion and exclusion criteria, followed by a full-text evaluation of potentially relevant studies. Any disagreements were resolved through discussion or consultation with a third reviewer. Only studies meeting all inclusion criteria were retained for the final synthesis to ensure methodological consistency and reliability.

Data extraction was conducted using a standardized PRISMA-based template, collecting information such as bibliographic details (authors, year, location), livestock species, technological approaches (AI algorithms and IoT infrastructure), application areas (disease detection, feed optimization, reproductive performance, welfare monitoring, mortality reduction), performance metrics (accuracy, precision, sensitivity, specificity, feed waste reduction, reproductive efficiency, mortality improvement), and reported challenges (cost, data security, interoperability).

To minimize bias, data extraction was performed independently by two reviewers and cross-checked for consistency. Extracted data were tabulated and synthesized descriptively. Due to substantial heterogeneity across livestock types, production scales, and performance indicators, a meta-analysis was not performed. Instead, a narrative synthesis approach was employed to identify major trends, performance ranges, and implementation outcomes.

The methodological quality of included studies was assessed using a customized appraisal framework for AI–IoT livestock research. The evaluation focused on five key dimensions: (1) transparency in describing AI–IoT system architecture, (2) methodological robustness including data validation strategies, (3) reproducibility of results, (4) quality of quantitative reporting, and (5) generalizability to real-world livestock settings. Each study was rated as high, moderate, or low quality, with only high and moderate studies included in the final synthesis to ensure analytical rigor and data reliability.

Overall, this methodological framework ensured a systematic, transparent, and replicable process, providing a comprehensive overview of current advancements and challenges in AI–IoT integration for precision livestock farming.

RESULTS AND DISCUSSION

This systematic review synthesized findings from 62 peer-reviewed studies published between 2023 and 2025, examining the application of Artificial Intelligence (AI) and Internet of Things (IoT) in livestock production. The integration of these technologies has demonstrated substantial quantitative improvements across multiple domains.

Operational and Health Performance

Machine learning algorithms achieved 85–95% accuracy in early disease detection. IoT- enabled systems reduced feed waste by 20– 35%, while reproductive efficiency increased by 15–25% and overall mortality decreased by 12–18% across species.

AI Applications in Monitoring

The Random Forest model used in *"Machine Learning to Predict Pregnancy in Dairy Cows"* achieved superior pregnancy prediction accuracy when incorporating environmental and behavioral variables.

The YOLOv8 + CBAM model in *"AI-Powered Cow Detection in Complex Farm Environments"* recorded 95.2% precision and a mean average precision (mAP@0.5:0.95) of 82.6%, even under variable lighting and occlusion conditions.

IoT-Based Feed and Resource Management

Integration of IoT sensors in smart feed systems (e.g., BinSentry and Soracom) enabled real-time feed inventory monitoring, reducing feed shortages and waste by approximately 25–30% through optimized refill scheduling.

Reproductive and Welfare Innovations

The *"AI-Based Intelligent Monitoring System for Estrus Prediction in the Livestock Industry"* (Cho & Kim, 2023) achieved 93% estrus detection accuracy in Hanwoo cattle using the Augmented Recognition Model (ARM).

The PAWS (Predictive Animal Welfare System) showed 88–90% accuracy in predicting infection risk, reducing mortality by 12–18% through early intervention.

Stakeholder Benefits

The integration of AI–IoT systems generated measurable outcomes 20% reduction in disease-related losses, 30% feed cost savings, and 15–25% increase in reproductive success rates indicating strong economic incentives for adoption.

- Training programs and technical support mechanisms
- User interface design principles (mobile apps, web dashboards)
- Feedback mechanisms and system customization options

Challenges Identified

Approximately 68% of reviewed studies were performed in controlled research environments, with only 32% conducted under commercial farm conditions. Major obstacles included dataset limitations, sensor durability issues, interoperability gaps, and high implementation costs.

Emerging Research Directions

Current experimental trends highlight development of low-cost, solar-powered IoT sensors, open-access datasets, and explainable AI (XAI) models to improve transparency and user trust. The results confirm that the integration of AI and IoT technologies has shifted Precision Livestock Farming (PLF) from an experimental phase into a practical, scalable framework. High accuracy rates in disease detection and significant reductions in feed waste demonstrate that data-driven systems can optimize both biological and economic performance. These findings align with global literature showing that AI–IoT adoption enhances resource efficiency, animal welfare, and sustainability in livestock management.

Computer Vision and Behavior Recognition

The successful applications of Random Forest and YOLO-based architectures underline how AI advancements have produced field-ready monitoring systems capable of operating under complex farm conditions. This technological maturity indicates that livestock monitoring can now rely on real-time analytics rather than manual supervision, reducing labor demands and improving animal welfare outcomes.

In Reproductive Management

In reproductive management, AI-driven estrus detection models such as ARM and health monitoring systems like PAWS exemplify how digital solutions can directly enhance fertility rates and welfare outcomes. The predictive capacities of these tools reduce reproductive inefficiencies and allow early intervention for diseases, improving herd productivity and welfare standards.

Stakeholder Implications

For stakeholders, these advancements present multiple implications. Producers gain tangible financial benefits, technology developers are encouraged to design adaptive and robust systems for various climates and species, and policymakers must address economic and regulatory barriers. Data governance, cybersecurity, and equitable technology access remain critical for scaling adoption among smallholder farmers.

Challenges and Constraints

However, persistent challenges such as limited datasets, lack of field validation, and interoperability constraints still hinder large- scale deployment. Most research is concentrated in high-resource settings, which raises questions about scalability and sustainability in developing regions. Economic constraints, ethical issues related to data ownership, and technical literacy gaps must be addressed through collaborative frameworks involving governments, academia, and industry.

Future Research Priorities

Looking ahead, research should emphasize longitudinal field trials, low-cost sensors, energy efficiency, and explainable AI to enhance user trust. Developing open-access datasets and international interoperability standards will be essential for global adoption. Ultimately, democratizing AI–IoT technologies in livestock farming will not only enhance productivity but also promote welfare-centered, environmentally sustainable animal agriculture.

Extended Analysis of Reviewed Studies

This systematic review analyzed 62 peer-reviewed studies published between January 2023 and June 2025 that integrated Artificial Intelligence (AI) and the Internet of Things (IoT) in livestock production systems. Overall, the findings confirm that the convergence of AI algorithms and IoT infrastructure has transformed livestock management from a conventional, experience-based system into a data-driven precision framework. Across multiple species—including cattle, swine, poultry, and small ruminants—AI–IoT integration has enhanced disease detection, reproductive performance, feed efficiency, and overall animal welfare. The collective evidence demonstrates that AI–IoT technologies can significantly improve operational precision and sustainability, though certain technical, economic, and ethical challenges persist.

Applications in Reproductive Monitoring

Recent studies have shown that AI and IoT are increasingly capable of real-time monitoring and prediction of animal health status. For instance, a 2023 study in *Porcine Health Management* evaluated an AI-driven estrus detection system for sows across three commercial farms in Belgium. The system integrated sensor data and image analysis to predict estrus onset with high reliability. The results showed a 4.3% increase in farrowing rate (FR), a 3.75% reduction in repeat-breeder cases, a 6.2% improvement in farrowing rate after first insemination (FRFI), and an average increase of 1.06 piglets per litter on one of the farms (Van den Bossche et al., 2023). These improvements indicate that AI-enhanced reproductive monitoring systems can reduce human error in estrus detection and optimize insemination timing. However, performance varied between farms due to differences in genetics, management practices, and insemination protocols, suggesting that AI performance may depend on context-specific adaptation.

Similarly, in dairy farming, deep learning-based visual recognition systems have shown remarkable success in identifying estrus and behavioral patterns. A 2023 study titled *Estrus Detection and Dairy Cow Identification with Cascade Deep Learning for Augmented Reality–Ready Livestock Farming* utilized a YOLOv5 model with region-of-interest cropping and augmented reality overlays to monitor Holstein cows. The system achieved a 99% accuracy rate in detecting mounting behavior, a 98% accuracy in identifying individual cows, and a 94% precision in detecting specific “mounting pairs” (Ali et al., 2023). Such systems are capable of reducing reliance on manual observation and can function continuously under farm conditions, providing early reproductive cues and enabling data synchronization with automated breeding management platforms.

In beef cattle, Cho and Kim (2023) proposed an *AI-Based Intelligent Monitoring System for Estrus Prediction in Hanwoo Cattle* using an Augmented Recognition Model (ARM). This system employed non-invasive video recognition to analyze behavioral and movement changes without requiring wearable sensors. The model achieved a 93% accuracy in estrus detection, outperforming traditional visual observation and step-counting methods. The researchers emphasized that the non-invasive nature of AI-based behavioral monitoring reduces stress on animals while providing more objective, data-driven reproductive management.

AI for Disease Detection and Health Monitoring

Beyond reproduction, AI and IoT have also revolutionized health monitoring. A 2023 *Phys.org* report on machine learning for early diagnosis of calf pneumonia demonstrated that IoT-enabled behavior sensors could predict disease occurrence up to four days before visual symptoms appeared. Using a dataset of behavioral activity, feeding patterns, and movement irregularities, the system achieved approximately 88% accuracy in identifying sick calves, and 70% of the cases were detected before traditional clinical diagnosis (Rutter et al., 2023). For chronic cases, accuracy improved to 80% within the first five days of disease onset. This early detection capacity is vital for minimizing antimicrobial use, reducing mortality, and preventing disease spread in group-housed systems.

Computer Vision and Behavior Recognition

The use of computer vision-based monitoring systems has also grown substantially in the context of animal detection and behavior recognition. A 2025 *arXiv* publication introduced the YOLOv8 + CBAM (Convolutional Block Attention Module) architecture for cow detection in complex farm environments. This hybrid model achieved 95.2% precision and a mean average precision (mAP@0.5:0.95) of 82.6% even under challenging lighting conditions and occlusion (Zhang et al., 2025). Such robust detection capabilities enable automatic tracking of cattle movement in real-world environments, contributing to more accurate health and welfare assessments. These systems represent the growing sophistication of AI architectures capable of handling the visual and environmental variability inherent in livestock farms.

IoT-Based Feed and Environmental Management

IoT-based systems have also been successfully applied to feed management and environmental monitoring. Smart feed inventory systems, such as BinSentry and Soracom, integrate IoT sensors to continuously measure feed levels and automate refill scheduling. According to Kumar et al. (2024), such systems reduce feed shortages and waste by 25–30% by optimizing feed delivery and minimizing overstocking. AI algorithms can analyze consumption trends, environmental data, and animal performance metrics to predict feed demand dynamically, improving both economic efficiency and sustainability. The ability to manage feed resources with real-time precision is particularly valuable given that feed costs typically account for 60–70% of total production expenses.

Animal Welfare Improvements

In terms of animal welfare, predictive systems such as PAWS (Predictive Animal Welfare System) have shown promising results. Studies between 2023 and 2024 demonstrated that PAWS could predict infection risks and stress levels with 88–90% accuracy, leading to a 12–18% reduction in mortality through early intervention (Li et al., 2024). This aligns with findings from AI–IoT studies that highlight improved welfare outcomes as a byproduct of early disease detection and optimized environmental management. AI-based pattern recognition enables farmers to identify subtle behavioral deviations, such as reduced movement or altered feeding, which are often the earliest indicators of illness or discomfort. 20% reduction in disease-related losses, 30% feed cost savings, 15–25% increase in reproductive success rates. These results indicate strong economic incentives for adoption (Singh et al., 2024).

Economic Impacts and Stakeholder Benefits

From an economic perspective, the integration of AI–IoT systems has yielded measurable benefits for stakeholders. Across multiple case studies, farms adopting AI-based reproductive monitoring reported 15–25% higher pregnancy rates and up to 30% feed cost savings due to optimized feeding schedules (Singh et al., 2024). Additionally, disease-related financial losses decreased by around 20% due to earlier detection and preventive treatment. These benefits provide strong economic incentives for large-scale adoption, particularly in commercial operations seeking to balance productivity with sustainability goals.

Limitations and Real-World Barriers

Nevertheless, significant challenges remain. About 68% of reviewed studies were conducted in controlled research environments, while only 32% took place in real commercial settings. This imbalance limits the generalizability of reported performance metrics. Most controlled studies involve ideal lighting, stable Wi-Fi connections, and close supervision—conditions rarely found in typical livestock farms. In real-world scenarios, sensor durability, data transmission stability, and environmental interference remain major obstacles. IoT sensors exposed to high humidity, dust, or temperature extremes often experience data loss or hardware degradation, compromising system reliability (Rahman et al., 2024).

Data Interoperability and Privacy Concerns

Interoperability and data management also pose substantial barriers. Many IoT systems operate using proprietary communication protocols, which restrict cross-platform integration. Data privacy and cybersecurity are emerging concerns as more farms adopt cloud-based monitoring solutions. Farmers remain hesitant to share operational data due to uncertainties regarding ownership and potential misuse (Nguyen & Patel, 2023). Additionally, the lack of standardized datasets limits the scalability of AI models across species and geographic regions. Current algorithms often rely on region-specific or species-specific datasets, which can reduce predictive accuracy when deployed elsewhere.

Technological Maturity and Advancements

Despite these limitations, the overall trajectory of AI–IoT development in livestock farming is positive. The successful application of deep learning architectures—such as Random Forest, Support Vector Machines, and YOLO-based models—demonstrates the growing maturity of these technologies. Random Forest models, for example, have shown robust performance in pregnancy prediction and disease classification, achieving over 90% accuracy in cross-validation tests (Wang et al., 2024). Deep learning models like YOLOv8 further extend the potential for real-time monitoring, combining visual analytics with sensor data for comprehensive health assessment.

IoT Infrastructure and Sustainability

IoT's role as the data infrastructure of precision livestock farming is equally crucial. Sensor networks, including accelerometers, GPS trackers, temperature probes, and smart collars, provide the continuous data streams necessary for AI algorithms to learn and adapt. Recent innovations include low-cost, solar-powered IoT sensors that address power and connectivity limitations in rural farms (Yuan et al., 2024). These advancements are expected to accelerate AI–IoT adoption in developing regions, where access to grid electricity and stable internet connectivity remains limited.

Environmental and Resource Management

The integration of AI and IoT has also advanced the sustainability agenda in agriculture. Smart environmental monitoring systems now measure ambient temperature, humidity, and air quality to maintain optimal living conditions for livestock. AI models can correlate environmental parameters with animal behavior and productivity, enabling predictive management of heat stress, feed intake, and disease risks. For instance, deep neural networks have been trained to forecast heat stress events in dairy cattle with over 90% precision, allowing proactive adjustments in cooling and ventilation systems (Silva et al., 2023). These applications support both animal welfare and environmental efficiency, contributing to the broader goals of sustainable livestock production.

From a policy and socio-economic standpoint, the widespread adoption of AI–IoT technologies could reshape livestock supply chains.

Socio-Economic and Policy Implications

Governments and agricultural institutions are increasingly recognizing the potential of digital livestock systems to improve traceability, biosecurity, and carbon-footprint management. However, the high upfront costs of sensor networks, maintenance, and data subscriptions pose barriers for smallholder farmers. The economic divide between industrial farms and small-scale producers could widen if affordable and localized solutions are not developed (Mendoza et al., 2024). Collaborative initiatives involving universities, private tech firms, and agricultural extension services are therefore critical for ensuring equitable access to these technologies.

Future Research Priorities

Looking ahead, several research directions emerge. First, future studies should emphasize large-scale field validation under diverse production conditions. Longitudinal field trials across various climates and management systems are necessary to evaluate long-term reliability, cost-effectiveness, and animal welfare impacts. Second, developing **explainable AI (XAI)** frameworks can enhance farmer trust by making algorithmic decisions transparent. Many current AI models are considered “black boxes,” limiting user understanding and confidence. Third, open-access datasets and global interoperability standards must be established to facilitate collaborative research and ensure model reproducibility. Initiatives like the *Global Open Livestock Data Commons (GOLDC)* proposed in 2024 are steps in this direction, aiming to standardize animal data formats and metadata structures for AI training and validation (Rodriguez et al., 2024).

Ethical and Environmental Considerations

Finally, ethical and environmental considerations must remain central to AI–IoT integration. Ethical AI frameworks in livestock should ensure data privacy, prevent algorithmic bias, and maintain a balance between productivity and welfare. Environmental sustainability should be measured not only by efficiency gains but also by reductions in waste, emissions, and resource consumption. Studies suggest that smart feeding systems and precision environmental controls can reduce methane emissions and feed waste by up to 20% compared to conventional operations (Lopez et al., 2024). Such findings underline the dual role of AI–IoT technologies in enhancing both economic and ecological outcomes.

Summary of Findings

In summary, the results of this review confirm that the integration of AI and IoT in livestock production between 2023 and 2025 has transitioned from experimental trials to commercially viable applications. AI models—particularly deep learning architectures—now provide reliable disease prediction, reproductive monitoring, and behavior recognition across species. IoT systems supply the essential real-time data infrastructure, enabling continuous monitoring and management automation. Quantitative gains reported across studies include disease detection accuracies of 85–95%, estrus prediction accuracies exceeding 90%, feed waste reduction of approximately 20–30%, reproductive efficiency gains of 10–20%, and mortality reductions of 10–15% in specific contexts.

However, realizing the full potential of AI–IoT technologies will require addressing persistent challenges related to data integration, hardware robustness, economic accessibility, and ethical governance. Research must continue to evolve toward open, explainable, and context-sensitive systems that benefit farms of all scales. As these technologies mature, their integration will not only enhance livestock productivity and profitability but also promote animal welfare, reduce environmental impact, and support the global transition toward sustainable, intelligent agriculture.

CONCLUSIONS AND SUGGESTION

Conclusions

The integration of Artificial Intelligence (AI) and Internet of Things (IoT) in livestock systems has proven to enhance productivity, efficiency, and animal welfare through accurate disease detection, optimized feeding, and improved reproductive performance. Despite these advancements, adoption remains limited by high costs, data interoperability issues, and unequal access, particularly among smallholders.

Suggestions

Future research should prioritize developing affordable, energy-efficient sensors, strengthening data governance, promoting digital literacy, and ensuring inclusive adoption to achieve sustainable and equitable Precision Livestock Farming.

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