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Review Article [OPEN ACCESS]

Artificial Intelligence for Precision Livestock Farming: A Systematic Review of Applications, Models, and Evaluation Metrics

Widyatasya Agustika Nurtrisha*, Luthfi Ramadani, Riska Yanu Fa'rifah, Faqih Hamami, Nur Ichsan Utama

ABSTRACT

The increasing demand for animal-based food products has intensified the need for efficient, data-driven livestock management practices. Artificial Intelligence (AI) has emerged as a key enabling technology within Precision Livestock Farming (PLF), supporting automated monitoring, prediction, and decision-making processes. This study presents a Systematic Literature Review (SLR) of AI applications in livestock farming, focusing on application domains, AI models, and evaluation metrics. Following the PRISMA 2020 guidelines, relevant studies published between 2013 and 2024 were systematically identified, screened, and assessed across major scholarly databases, resulting in 20 eligible articles for qualitative synthesis. The findings indicate that AI is primarily applied to animal identification, body weight estimation, disease detection, behavior analysis, and feed management. Deep learning models, particularly Convolutional Neural Networks, dominate image-based tasks, while traditional machine learning approaches remain effective for structured sensor and tabular data. Common evaluation metrics include accuracy, precision, recall, R^2, and Mean Absolute Error. Despite promising results, the review reveals substantial heterogeneity in datasets, evaluation protocols, and livestock sector coverage, which limits cross-study comparability. This review highlights methodological trends, identifies key research gaps, and provides insights to guide future AI-driven PLF research and implementation.

Keyword: Artificial intelligence, precision livestock farming, systematic literature review

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Corresponding Author: Widyatasya Agustika Nurtrisha, Department of Information System, Telkom University, Indonesia, widyatasya@telkomuniversity.ac.id
Authors: Luthfi Ramadani, Department of Information System, Telkom University, Indonesia, luthfi@telkomuniversity.ac.id; Riska Yanu Fa'rifah, Department of Information System, Telkom University, Indonesia, riskayanu@telkomuniversity.ac.id; Faqih Hamami, Department of Information System, Telkom University, Indonesia, faqihhamami@telkomuniversity.ac.id; Nur Ichsan Utama, Department of Information System, Telkom University, Indonesia, nichsan@telkomuniversity.ac.id

1. INTRODUCTION

The livestock sector in Indonesia has continued to demonstrate positive growth and remains strategically important for national food security, particularly in meeting the increasing demand for animal-based food products driven by population growth. Despite this potential, domestic livestock production has not yet fully satisfied national consumption needs. Official statistics from Statistics Indonesia indicate persistent deficits in beef and buffalo meat availability, amounting to 294.62 thousand tons in 2020 and 270.98 thousand tons in both 2021 and 2022 (Badan Pusat Statistik, 2020, 2021). These shortages highlight structural challenges in national livestock production systems and underscore the need for improved efficiency, productivity, and monitoring across the sector. Similar issues have also been observed in other livestock commodities, such as purebred chicken production, which experienced a decline in demand of 0.11% alongside production deficits in early 2022.

Addressing these challenges requires comprehensive and timely information to support effective livestock management and decision-making. Key data include livestock population statistics, production and consumption levels, market prices, and input requirements, as well as continuous monitoring of operational activities such as feed management, animal health status, body weight development, and product quality. In conventional livestock systems, the collection and analysis of such data are often fragmented and labor-intensive, limiting their usefulness for precision-oriented management. Consequently, there is an increasing need for technological solutions capable of integrating real-time data acquisition with automated analysis to support more responsive and evidence-based livestock production practices.

As population growth continues to drive demand for meat, milk, and eggs, technological interventions become essential to enhance production capacity while maintaining animal welfare and product quality. Recent advances in sensing technologies and artificial intelligence have enabled automated detection of animal weight, growth stages, and health conditions, as well as optimized feed monitoring and evaluation of feeding impacts on livestock performance (Patel et al., 2022). These capabilities form the foundation of Precision Livestock Farming (PLF), which aims to improve efficiency, reduce waste, and support sustainable livestock management through data-driven approaches.

A growing body of research has explored the application of Artificial Intelligence (AI) in livestock farming, particularly for tasks such as animal identification, behavior analysis, disease detection, and health monitoring using Machine Learning (ML) and Deep Learning (DL) techniques (García et al., 2020; Hossain et al., 2022; Qiao et al., 2021). However, much of the existing literature focuses on specific use cases or individual livestock species, offering limited cross-sectoral synthesis. Moreover, many prior studies emphasize technological feasibility without systematically comparing model performance or evaluation metrics across different livestock contexts. This fragmentation limits the ability of researchers and practitioners to derive broader methodological insights or identify consistent research gaps.

To address this limitation, a systematic synthesis of existing studies is required. This study therefore conducts a Systematic Literature Review (SLR) to examine AI applications within the Precision Livestock Farming domain. Unlike prior reviews that predominantly provide descriptive summaries of technologies and application areas, this review adopts a performance-oriented perspective by analyzing AI models, application domains, and evaluation metrics across livestock sectors. By systematically reviewing studies published between 2013 and 2024, this paper aims to identify prevailing methodological trends, assess the effectiveness of ML and DL approaches, and highlight unresolved challenges and research opportunities. Through this synthesis, the study seeks to clarify the role of AI in enhancing productivity, monitoring capabilities, and livestock output quality, with implications for both research and practical implementation in livestock systems.

2. LITERATURE REVIEW AND METHODS

This study adopts a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize relevant studies related to artificial intelligence applications in livestock farming. The review process follows the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure transparency, reproducibility, and methodological rigor. The SLR methodology enables a structured synthesis of prior research findings, allowing comprehensive insights to be drawn from a broad body of literature.

In accordance with established SLR procedures, the review process was conducted through three main stages: planning, conducting, and reporting, as outlined by Kitchenham & Charters (2007). The planning stage involved defining the research scope and formulating search strategies, including the identification of relevant keywords and research questions. Literature searches were performed across multiple scholarly databases, including IEEE Xplore, ScienceDirect, Scopus, and other relevant sources that matched the predefined search criteria.

The conducting stage encompassed the systematic retrieval of publications, screening and selection of eligible studies based on inclusion and exclusion criteria, and structured data extraction from the selected articles. Finally, the reporting stage focused on synthesizing the extracted data to identify research trends, application domains, AI models, and evaluation metrics. The overall SLR workflow applied in this study is illustrated in Figure 1.

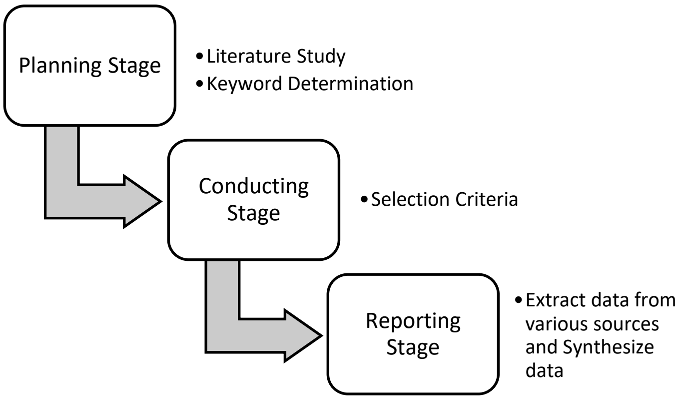

Figure 1. Systematic literature review process adapted from Kitchenham & Charters (2007)

2.1 Research Questions

This SLR focuses on the application and implementation of AI technologies within the livestock sector. To ensure analytical clarity and maintain a well-defined research scope, this study formulates explicit research questions that guide the literature selection, analysis, and synthesis processes. The answers to these research questions are derived from empirical evidence reported in the selected primary studies.

Based on the objectives of the review, four research questions (RQs) are defined, as summarized in Table 1. These questions are designed to capture the problem domains addressed by AI, the performance of AI models, the diversity of livestock sectors, and the evaluation approaches adopted in prior research.

Table 1. Research Questions (RQs)

Research Area	Research Question
Problem Definition	**RQ1:** What livestock farming problems can be addressed using AI-based approaches?
Performance Improvement	**RQ2:** Which machine learning and deep learning models demonstrate the best performance in addressing specific on-farm problems?
Sectoral Variation	**RQ3:** How is AI applied across different livestock sectors?
Model Evaluation	**RQ4:** What evaluation metrics and AI approaches are commonly used in livestock farming studies?

2.2 Search Strategy and Selection Criteria

The search strategy was designed to identify relevant and high-quality studies that address the research questions defined in this review. Literature searches were conducted across multiple scholarly databases, including IEEE Xplore, ScienceDirect, Scopus, and Google Scholar. These databases were selected to ensure broad coverage of peer-reviewed research in artificial intelligence, computer science, and livestock-related applications. The search process involved the use of predefined keywords and the examination of citation trails and publisher records to capture potentially relevant studies.

Study selection was performed through a systematic screening process based on predefined inclusion and exclusion criteria. Records retrieved from all databases were compiled into a spreadsheet to facilitate duplicate removal and eligibility assessment. Studies were included only if they directly addressed the research questions of this review, while publications that were not aligned with the research scope were excluded. This structured approach ensured consistency and transparency throughout the selection process.

Following study selection, relevant data were extracted from the included articles to support the synthesis of findings. Data extraction focused on key attributes such as AI application domains in livestock farming, publication year, publication venue, AI models employed, performance metrics, and evaluation approaches. The extracted data were then categorized and synthesized in accordance with the corresponding research questions to enable systematic analysis. Based on the defined research questions, the inclusion and exclusion criteria applied in this review are summarized in Table 2.

Table 2. Selection criteria

Inclusion Criteria	**Exclusion Criteria**
Studies published between 2013 and 2024	Studies not related to AI or livestock farming
Studies written in English	Non-scientific documents
Journal articles or conference papers focusing on AI applications in livestock farming	Duplicate publications across databases

The initial search process retrieved 35 studies. These records were subsequently screened for relevance and quality, with duplicate entries removed. Eligibility was assessed based on the defined selection criteria, resulting in the final set of studies included in the review. The overall selection process, from identification to inclusion, is summarized using a PRISMA flow diagram presented in Figure 2.

2.3 Data Extraction and Coding

Following the final study selection, relevant information from each included article was manually extracted using a structured spreadsheet. The extracted data comprised publication year and source, author information and country of origin, livestock type, and the AI techniques or algorithms employed (e.g., machine learning, deep learning, or hybrid approaches). In addition, information regarding research objectives or application domains—such as weight estimation, disease diagnosis, behavior recognition, and feed management—was collected, along with evaluation metrics and key findings.

To support systematic analysis, each extracted variable was coded and categorized in accordance with the corresponding research questions (RQ1–RQ4). This coding scheme facilitated comparative analysis across studies and enabled a structured synthesis of findings aligned with the objectives of the review.

2.4 Quality Assessment

All studies that met the inclusion criteria and addressed the defined research questions were considered relevant and subjected to a quality assessment process. The purpose of this assessment was to ensure that only studies of sufficient academic quality were included in the final synthesis. Quality evaluation was conducted based on predefined assessment questions derived from the inclusion and exclusion criteria.

The quality assessment criteria applied in this review are as follows:

QA1: Was the publication released within the period 2013–2024?

QA2: Does the publication focus on artificial intelligence technologies applied to livestock farming?

QA3: Is the study published in the English language?

QA4: Is the publication a peer-reviewed journal article or conference proceeding?

Only studies that satisfied these quality assessment criteria were retained for further analysis and synthesis.

2.5 Data Synthesis

Data synthesis constitutes a central component of the analytical phase of this study, serving to integrate findings from the selected literature in relation to the defined research focus. The primary objective of the synthesis process is to consolidate empirical evidence addressing Research Questions RQ1 through RQ4. Accordingly, the included studies were required to explicitly report the application of AI techniques in livestock farming and to describe how such technologies are implemented across different livestock sectors.

The literature search covered publications from 2013 to 2024 and employed combinations of predefined keywords, including *"Artificial Intelligence"*, *"Machine Learning"*, *"Deep Learning"*, *"Livestock Farming"*, *"Precision Livestock Farming"*, and *"Smart Farming"*. These keywords were selected to capture a comprehensive range of AI-driven approaches relevant to precision-oriented livestock management.

The initial search identified 35 records across four databases: IEEE Xplore, ScienceDirect, Scopus, and Google Scholar. After the removal of five duplicate records, 30 studies remained for further screening. During the screening phase, seven articles were excluded based on title and abstract review due to their limited relevance to AI applications in livestock farming. The remaining 23 articles were subjected to an eligibility assessment, resulting in the exclusion of three additional studies that did not meet the inclusion criteria, such as non-English publications or conceptual papers lacking empirical evidence. Ultimately, 20 studies satisfied all four Quality Assessment (QA) criteria and were included in the qualitative synthesis of this review. The overall study selection process, from identification to final inclusion, is illustrated in Figure 2 using a PRISMA 2020 flow diagram.

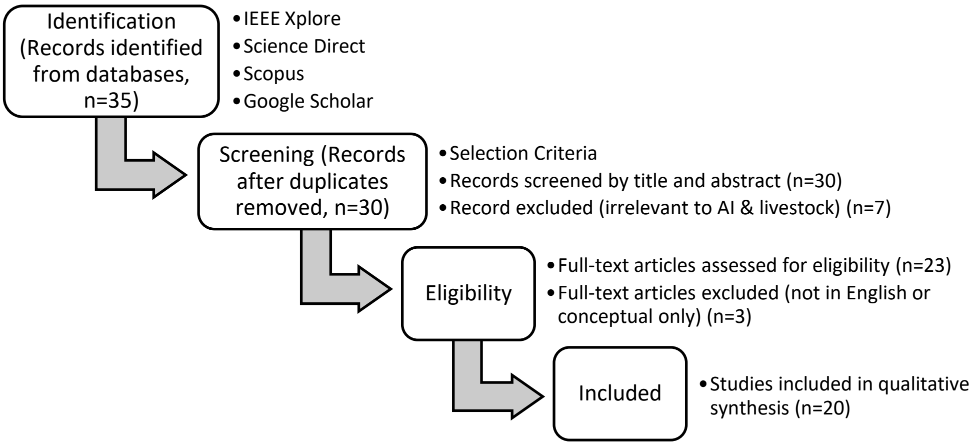

Figure 2. Flow diagram of the study selection process for the systematic literature review (adapted from PRISMA 2020; Page et al. (2021))

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

The literature search conducted across multiple academic databases, including IEEE Xplore, ScienceDirect, Scopus, and other relevant sources, yielded a diverse set of publications addressing artificial intelligence applications in livestock farming. Following the screening and quality assessment procedures, a total of 20 studies were selected for inclusion in the final synthesis. These studies represent a range of livestock contexts, encompassing cattle farming, poultry production, swine management, and general PLF systems.

Most of the selected studies adopted quantitative and experimental research designs, frequently integrating image-based data, sensor measurements, or Internet of Things (IoT)-enabled monitoring systems. The predominant AI techniques reported in the literature include Convolutional Neural Networks (CNNs) for image and video analysis, Support Vector Machines (SVMs) for classification tasks, and various regression models for prediction-oriented applications. From a conceptual perspective, the majority of studies are grounded in the Precision Livestock Farming paradigm, often supported by theoretical foundations from computer vision and data-driven decision-support systems.

To facilitate systematic analysis, the selected publications were classified based on key attributes, including research title, author(s), data source, year of publication, and compliance with the predefined

Quality Assessment (QA) criteria. This classification provides an overview of the distribution of studies across databases and their methodological eligibility. The results of the publication classification and quality assessment are summarized in Table 3.

Table 3. Paper classification results based on quality assessment criteria

Author	Source	QA1	QA2	QA3	QA4
(Paputungan et al., 2013)	Scopus	Y	N	Y	Y
(Memon et al., 2016)	IEEEXplore	Y	N	Y	Y
(Lao et al., 2016)	Science Direct	Y	N	Y	Y
(Andrew et al., 2017)	IEEEXplore	Y	Y	Y	Y
(Debauche et al., 2018)	Scopus	Y	N	Y	Y
(Campos et al., 2019)	Science Direct	Y	N	Y	Y
(Anifah & Haryanto, 2020)	IEEEXplore	Y	Y	Y	Y
(Gjergji et al., 2020)	IEEEXplore	Y	Y	Y	Y
(García et al., 2020)	Science Direct	Y	Y	Y	Y
(Benaissa et al., 2020)	Science Direct	Y	N	Y	Y
(Neethirajan & Kemp, 2021)	Science Direct	Y	N	Y	Y
(Z. Wang et al., 2021)	Scopus	Y	Y	Y	Y
(Qiao et al., 2021)	Science Direct	Y	Y	Y	Y
(Easwaran et al., 2021)	Scopus	Y	N	Y	Y
(Mahmud et al., 2021)	Science Direct	Y	Y	Y	Y
(A. N. Ruchay et al., 2021)	Scopus	Y	Y	Y	Y
(Mittal, 2021)	Scopus	Y	Y	Y	Y
(Bao & Xie, 2022)	Science Direct	Y	Y	Y	Y
(Hossain et al., 2022)	Science Direct	Y	Y	Y	Y
(Fuentes et al., 2022)	Scopus	Y	Y	Y	Y
(Patel et al., 2022)	Google Scholar	Y	Y	Y	N
(Shephard et al., 2022)	Science Direct	Y	N	Y	Y
(Na et al., 2022)	Scopus	Y	Y	Y	Y
(A. Ruchay et al., 2022)	Scopus	Y	Y	Y	Y
(Pretto et al., 2024)	Science Direct	Y	Y	Y	Y
(Alzubi & Galyna, 2023)	IEEEXplore	Y	Y	Y	Y
(Cho & Kim, 2023)	Scopus	Y	Y	Y	Y
(Jiang et al., 2023)	Scopus	Y	N	Y	Y
(Osrof et al., 2023)	Science Direct	Y	N	Y	Y
(Y. Wang et al., 2023)	Science Direct	Y	N	Y	Y
(El-Ghamry et al., 2023)	Science Direct	Y	Y	Y	Y
(Chen et al., 2023)	Science Direct	Y	Y	Y	Y
(Rana et al., 2023)	Google Scholar	Y	N	Y	Y
(Backman et al., 2023)	Science Direct	Y	Y	Y	Y
(Bezas & Filippidou, 2023)	Google Scholar	Y	Y	Y	N

3.2 Findings by Research Questions (RQs)

To systematically examine the methodological landscape of AI in PLF, this review categorizes AI approaches into two broad groups: deep learning–based methods and traditional machine learning–based methods. This classification facilitates a structured comparison of model suitability across different data modalities, problem types, and livestock sectors. The findings are presented according to the four research questions defined in Section 2.1.

RQ1: What livestock farming problems can be addressed using AI-based approaches?

The reviewed studies indicate that AI has been widely applied to address key operational challenges in livestock management. Common application areas include animal identification, body weight estimation, disease detection, behavior monitoring, and feed management. For example, Gjergji et al. (2020) and Na et al. (2022) employed computer vision–based models to estimate animal body weight, while Benaissa et al. (2020) utilized sensor-driven AI systems to detect calving and estrus behavior in dairy cattle. Collectively, these applications demonstrate that AI-based solutions can support improved monitoring accuracy, enhanced animal welfare, and more efficient farm management practices.

RQ2: Which machine learning and deep learning models demonstrate the best performance in addressing specific on-farm problems?

Across the selected studies, deep learning (DL) models—particularly Convolutional Neural Networks (CNNs) and deep regression architectures—consistently achieved superior performance in image-based tasks, such as livestock detection and body weight prediction (Pretto et al., 2024; A. Ruchay et al., 2022). In contrast, traditional Machine Learning (ML) models, including Support Vector Machines (SVMs), Random Forests, and Bayesian Ridge Regression, were more effective when applied to structured sensor data or tabular datasets (Anifah & Haryanto, 2020; Na et al., 2022). These findings suggest that model performance is strongly influenced by data characteristics and task complexity, underscoring the importance of aligning AI techniques with appropriate data modalities.

RQ3: How is AI applied across different livestock sectors?

AI applications span multiple livestock sectors, with cattle farming representing the dominant focus, accounting for more than 60% of the reviewed studies. Research in this domain primarily addresses weight estimation, health monitoring, and behavior analysis. Poultry farming studies frequently emphasize feed optimization and environmental control, while swine farming research predominantly focuses on behavior recognition using image processing techniques (Lao et al., 2016). In addition, the integration of IoT technologies and cloud-based platforms has been shown to enhance real-time data acquisition and system scalability across livestock sectors (Debauche et al., 2018).

RQ4: What evaluation metrics and AI approaches are commonly used in livestock farming studies?

Performance evaluation in the reviewed literature commonly relies on metrics such as accuracy, precision, recall, coefficient of determination (R^2), and Mean Absolute Error (MAE). Most studies assessed model effectiveness by benchmarking predictive performance using datasets collected from real farm environments. Deep learning approaches generally outperformed traditional ML methods in vision-based recognition tasks, whereas hybrid systems that combine ML models with IoT sensor data offered more balanced performance for real-time monitoring applications (Alzubi & Galyna, 2023).

3.3 Evaluation Metrics and Model Performance in Precision Livestock Farming

Building on the comparative analyses presented in RQ2 and RQ4, this subsection synthesizes the evaluation metrics and performance characteristics of AI models applied within the PLF context. The synthesis identifies recurring patterns associated with data modalities, model categories, and reported performance outcomes across the reviewed studies.

Deep learning–based approaches, particularly Convolutional Neural Networks (CNNs), were predominantly employed for image-centric tasks, including livestock detection, body weight estimation, and behavior recognition (Gjergji et al., 2020; Pretto et al., 2024; A. Ruchay et al., 2022). These studies consistently reported high levels of accuracy, precision, and recall, underscoring the suitability of CNN architectures for visual recognition problems in PLF environments. The strong performance of deep learning models is largely attributable to their capacity to automatically extract hierarchical features from high-dimensional visual data.

In contrast, traditional machine learning models—such as Support Vector Machines, Random Forests, and Bayesian Ridge Regression—were more frequently applied to structured sensor data and tabular datasets (Anifah & Haryanto, 2020; Na et al., 2022). Model performance in these studies was commonly evaluated using regression-oriented metrics, including Mean Absolute Error (MAE) and the coefficient of determination (R^2). While these approaches generally yielded stable and interpretable predictive performance, they also offered lower computational complexity compared to deep learning models, making them suitable for resource-constrained or real-time monitoring scenarios.

Despite the reported performance gains, substantial variability exists across the reviewed studies in terms of dataset characteristics, evaluation metrics, and experimental configurations (García et al., 2020; Mahmud et al., 2021). This heterogeneity limits direct cross-study comparisons and poses challenges for generalizing findings. The lack of standardized benchmark datasets and unified evaluation protocols remains a significant barrier to reproducible and comparable performance assessment in AI-driven Precision Livestock Farming systems.

3.4 Discussion

The findings of this review indicate that the implementation of AI, ML, and DL in livestock farming primarily concentrates on two critical domains: feed management and animal health monitoring. AI-driven feed management applications commonly employ ML techniques to support diet optimization, feed intake monitoring, and land or resource management. These applications aim to enhance feeding efficiency while minimizing waste and production costs. In parallel, AI-based health monitoring systems are widely used for disease detection, physiological condition assessment, and early warning of health-related anomalies, thereby contributing to improved animal welfare and overall farm productivity.

Several studies emphasize the integration of AI with IoT and cloud-based infrastructures to support continuous livestock monitoring. For example, Debauche et al. (2018) proposed an IoT-enabled cloud architecture that aggregates sensor data and presents monitoring results through a web-based dashboard, facilitating real-time decision support for farmers. Similarly, Andrew et al. (2017) developed a computer vision–based monitoring system using drone imagery and deep neural networks to automatically detect Holstein Friesian cattle, demonstrating the potential of aerial data and DL models for large-scale livestock observation.

In addition to general monitoring, AI has been increasingly applied to reproductive management, where accurate detection of calving and estrus events is essential for optimizing breeding strategies and maintaining animal health. Timely identification of these reproductive phases enables farmers to implement appropriate interventions that support livestock welfare and reproductive efficiency. Benaissa et al. (2020) employed a Logistic Regression model based on sensor-derived behavioral data to detect calving and estrus events, evaluating detection performance across multiple temporal windows ranging from 24 hours to 2 hours prior to calving.

Beyond health and reproduction, AI-based livestock studies have also addressed feeding behavior and intake estimation. Ingestive behavior, which reflects chewing and feeding activity, provides valuable indicators for estimating fiber consumption in ruminants. Campos et al. (2019) proposed a non-invasive approach using a surface electromyography (sEMG)-based sensor system to capture muscle activity signals associated with feeding behavior in ruminants such as cattle, sheep, and deer. Related behavioral analysis has also been conducted in swine farming, where Lao et al. (2016) examined sow behavior during pregnancy and lactation using image-based monitoring techniques. These studies collectively highlight the growing role of AI in capturing fine-grained behavioral indicators to support data-driven livestock management.

3.5 Implications and Future Directions

The reviewed studies indicate that AI applications in livestock farming have evolved from isolated predictive models into integrated intelligent systems that combine sensors, cloud computing, and Internet of Things (IoT) technologies, reflecting a broader shift toward data-driven and automated livestock management. Despite this progress, several methodological limitations persist across the literature, including data heterogeneity arising from small or locally collected datasets, the absence of standardized benchmark datasets and unified evaluation metrics, and an uneven research focus that remains heavily concentrated on cattle farming while other livestock sectors, such as poultry, sheep, and swine, are comparatively underrepresented.

Nevertheless, the convergence of AI, IoT, and computer vision technologies marks a clear transition toward Precision Livestock Farming, enabling real-time monitoring, early anomaly detection, and semi-automated decision support aligned with global trends in sustainable agriculture and smart farming. From a theoretical and practical perspective, this review reinforces the role of machine learning and deep learning within the PLF framework and underscores their potential to enhance livestock productivity and animal welfare. Future research should emphasize the use of larger and openly accessible datasets for benchmarking, explore hybrid AI–IoT architectures for real-time prediction and disease prevention, and incorporate economic as well as environmental evaluations to assess the long-term sustainability of AI-driven livestock systems.

4. CONCLUSION

This Systematic Literature Review (SLR) demonstrates that Artificial Intelligence technologies play an increasingly important role in supporting livestock farming activities. The reviewed studies indicate that AI-based approaches contribute to improvements in livestock product quality, disease diagnosis, body condition assessment, and animal weight estimation. In particular, deep learning techniques are widely applied to image-based tasks such as livestock detection and segmentation, while machine learning methods are commonly used within the Precision Livestock Farming framework to support identification, monitoring, and decision-support processes.

Overall, the findings highlight the potential of AI-driven solutions to enhance efficiency, accuracy, and sustainability in livestock management. However, the review also suggests that further research is needed to address limitations related to data heterogeneity, evaluation consistency, and sectoral coverage. Future studies should focus on developing standardized benchmarks, expanding applications beyond dominant livestock sectors, and promoting scalable AI implementations that support robust and practical adoption in real-world livestock systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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