Review Article

Poultry Systems: A Systematic Review on IoT, Artificial Intelligence, and Multimodal Technologies for Precision Poultry Farming

Jopeth Cahanap [1], Lyn Abalde [1], Divilyn Sambulan [1], Ramil Entana Jr. [1,*]

Received: 25 May 2026; Revised: 05 July 2026;
Accepted: 20 July 2026; Published: 23 July 2026

DOI: https://doi.org/10.66074/J5Y9M4Z2

Abstract
The global poultry industry faces increasing pressure to improve production efficiency, reduce environmental impacts, and meet stricter animal welfare standards. Conventional manual monitoring methods are increasingly inadequate for addressing the complexities of large-scale commercial poultry production. This systematic review synthesizes current evidence on the effectiveness of smart technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), computer vision, acoustic monitoring, and robotics, in advancing precision poultry farming. Following PRISMA 2020 guidelines, 39 peer-reviewed studies published between 2020 and 2026 were systematically identified, screened, and analyzed using thematic synthesis across five major technological domains. The geographical distribution of research revealed a strong concentration of studies in Asia, highlighting the region's leading role in the development and implementation of smart poultry farming technologies, while also indicating the need for broader geographic representation in future research. Findings revealed that IoT-based environmental monitoring is the most mature technology, with reported accuracies ranging from 93.7% to over 99%. AI-driven disease detection has also advanced rapidly, with YOLO-based models achieving 0.964 precision and more than 90% mean average precision. Acoustic monitoring systems, such as SmartEars, outperformed human veterinary experts under real farm noise conditions, achieving 96.03% accuracy compared with 85–93%. In contrast, robotics and big data

[1] Mindanao State University-Zamboanga Sibugay, Philippines
*ramiljr.entana@msubuug.edu.ph

Volume 2, Issue 3, September 2026

integration remain largely in prototype and early-development stages. Despite substantial progress, major barriers to large-scale adoption persist, including limited long-term field validation, inadequate inclusion of smallholder systems, lack of standardized datasets, weak multimodal data integration, and insufficient ethical oversight. Overall, smart poultry technologies demonstrate strong potential to improve precision management, productivity, and animal welfare. Future research should prioritize commercial-scale validation, inclusive technology design, standardized datasets, stronger multimodal integration, and robust ethical and regulatory frameworks to support sustainable adoption in modern poultry systems.

Keywords: artificial intelligence, Internet of Things, multimodal technologies, precision livestock farming, smart poultry farming

1. Introduction

The global poultry industry occupies a central position in global food security, producing over 120 million tons of poultry meat and billions of eggs annually to sustain a rapidly expanding population (Shomina & Beltrán-Alcrudo, 2025). As demand for animal-derived protein continues to intensify alongside population growth and rising incomes in developing economies, the poultry sector faces increasing pressure to improve production efficiency, minimize environmental impact, and comply with more stringent animal welfare regulations (Franzo et al., 2023).

Traditional poultry farming methods, which rely heavily on manual observation and labor-intensive interventions, are increasingly inadequate for the scale and complexity of modern commercial production systems, where millions of birds may be housed within a single facility (Singh et al., 2020). Consequently, the need for smarter farming approaches capable of detecting early signs of disease, maintaining stable environmental conditions, and optimizing feed conversion has become both economically significant and ethically imperative (Ojo et al., 2022).

The emergence of Precision Livestock Farming offers a comprehensive response to these challenges. Smart farming is broadly defined as the application of digital information technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), machine learning, computer vision, acoustic analytics, robotics, and big data platforms to agricultural production systems (Olejnik et al., 2022). Evidence from recent studies suggests that these technologies can reduce mortality rates, lower disease incidence, improve feed conversion efficiency, and enhance the detection of welfare-compromising conditions at a scale and precision beyond human capability (Natsir et al., 2025).

Despite this promising progress, the current literature remains highly fragmented. While some studies focus on environmental sensor systems, others emphasize image-based disease detection, vocalization analysis, robotics, or integrated data platforms. Moreover, many published studies remain limited to preliminary experiments or small-scale validations rather than long-term commercial field evaluations (Bhandekar et al., 2023). As a result, there is a critical need for a comprehensive synthesis that not only documents existing technological developments but also distinguishes mature, field-tested applications from emerging laboratory-based prototypes and identifies areas where evidence remains demonstrating that high performance under controlled conditions may not consistently achieve similar outcomes in real-world poultry production environments.

Therefore, this systematic review was conducted to identify the smart technologies currently applied in poultry farming; to synthesize evidence on their effectiveness, accuracy, and practical outcomes; to compare findings across studies, including methodological similarities, differences, and contradictions; and to identify major research gaps and propose recommendations for future research and practical implementation. Furthermore, beyond its technological relevance, this review aligns with several United Nations Sustainable Development Goals, particularly SDG 2 (Zero Hunger) through improved food security and sustainable poultry productivity, SDG 9 (Industry, Innovation and Infrastructure) through the advancement of intelligent agricultural technologies, SDG 12 (Responsible Consumption and Production) through more efficient use of feed, energy, and water resources, and SDG 13 (Climate Action) by supporting environmentally sustainable and resource-efficient poultry production systems. By promoting precision, efficiency, and welfare-oriented management, smart poultry farming also contributes to broader global efforts toward resilient and sustainable food systems.

2. Methodology

2.1 Research Design

This study employed a systematic literature review (SLR) approach guided by the PRISMA framework to systematically identify, evaluate, and synthesize existing evidence on smart poultry farming technologies. The review focused on studies published between January 2020 and April 2026, ensuring the inclusion of recent and relevant research addressing the integration of intelligent technologies in poultry systems. Data extraction, analysis, and synthesis were conducted in April 2026 to May 2026, encompassing both global and national research contexts.

2.2 Data Collection

A systematic literature search was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Relevant studies were retrieved from peer-reviewed academic databases, including Google Scholar, Elsevier ScienceDirect, DOAJ, DOAB, IEEE Xplore, and Crossref. The search strategy combined poultry farming-related terms with emerging technology-related keywords using Boolean operators. The primary search string was: ("smart poultry farming" OR "precision poultry farming" OR "precision livestock farming") AND ("Internet of Things" OR "IoT" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "acoustic monitoring" OR "robotics" or "big data"). Equivalent search strings were adapted as necessary to match the indexing and search requirements of individual databases.

2.3 Eligibility Criteria

Studies were included if they met the following criteria: (1) published between January 2020 and April 2026; (2) written in English; (3) focused on the application of digital, intelligent, or automated technologies within poultry production systems; and (4) provided sufficient methodological and technical information relevant to precision poultry farming. Eligible sources primarily consisted of peer-reviewed journal articles; however, selected conference proceedings, technical reports, datasets, and other scholarly sources were also considered when they present novel technologies, methodological innovations, or emerging applications not yet extensively represented in the peer-reviewed literature. Studies were excluded if they: (1) focused primarily on livestock species other than poultry; (2) lacked a clearly defined technology application or measurable outcome; (3) were published outside the defined review period; or (4) provided insufficient methodological information for evaluation.

2.4 Selection Process

Study selection followed the PRISMA screening process. The initial database research identified 67 records. After removing 12 duplicates, 55 unique records underwent title and abstract screening. During this stage, 6 studies were excluded due to insufficient poultry relevance, limited methodological transparency, unclear technological application, or failure to meet the review timeframe. The remaining 49 full-text articles were assessed for eligibility, resulting in the exclusion of 10 studies. A total of 39 studies were ultimately included in the final qualitative synthesis (Figure 1).

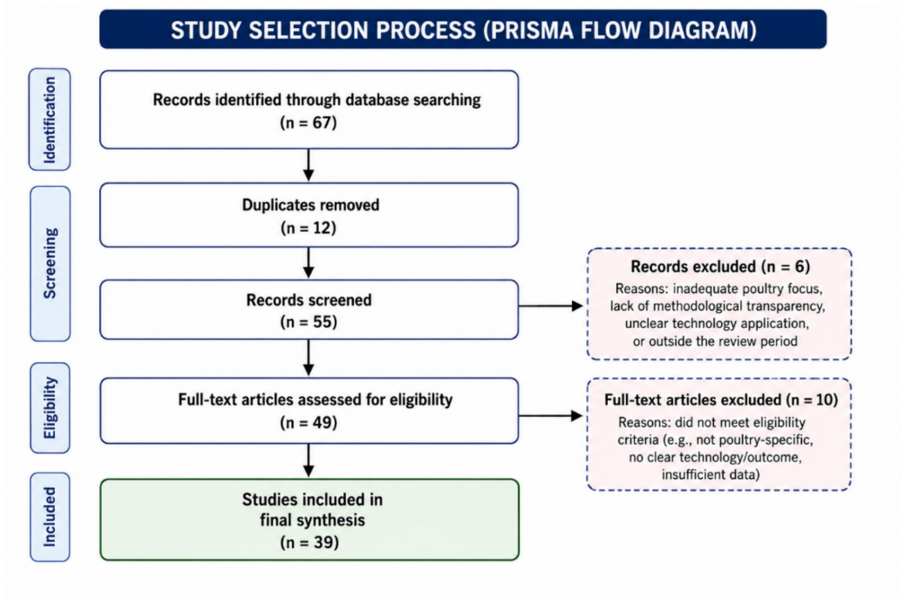

Figure 1. Schematic diagram of the study selection process.

2.5 Data Analysis

Data extraction was conducted using thematic content analysis to identify recurring patterns, technological trends, methodological differences, and existing research gaps. Extracted variables included publication year, country of origin, study design, technology type, hardware and software used, dataset characteristics, experimental setting, poultry type, performance indicators, and principal findings. For studies involving multiple technologies, each technological component was analyzed separately. Due to the methodological heterogeneity of the included studies, including prototypes, laboratory validations, field deployments, and review articles, risk bias was assessed qualitatively.

The selected studies were categorized into five thematic domains: (1) IoT-based environmental monitoring and control; (2) AI and machine learning for disease detection and health management; (3) computer vision and behavioral analysis; (4) acoustic monitoring and vocalization analysis; and (5) robotics, automation, and big data integration. Findings within each domain were comparatively synthesized to identify consistencies, contradictions, and development trends over time. A statistical meta-analysis was not performed due to substantial heterogeneity in study designs and reported outcome measures.

2.6 Quality Assessment

To evaluate the methodological rigor of the included studies, a qualitative quality assessment was conducted. Each study was assessed according to the following criteria: (1) clarity of research objectives; (2) adequacy of dataset size or sample population; (3) transparency of methodological procedures; (4) validation approach (laboratory testing, pilot implementation, or field validation); (5) reporting of performance metrics; (6) applicability to real-world poultry production systems.

The selected studies were categorized as high, moderate, or low methodological quality. High-quality studies demonstrated clear methodologies, robust validation procedures, adequate datasets, and practical applicability in commercial or field settings. Moderate-quality studies reported satisfactory methodological details but were limited by smaller datasets, controlled experimental conditions, or restricted validation procedures.

The quality assessment was used to guide interpretation of the findings and to distinguish between early-stage prototype studies and technologies that have undergone extensive validation under commercial poultry production conditions.

3. Results

3.1 Study Characteristics

The thirty-nine (39) included studies cover the 2020–2026 period and show a clear progression in both scale and sophistication. Early papers mostly described sensors, and by 2022, more studies used structured Machine Learning workflows. From 2023 onward, deep learning, edge AI, multimodal monitoring, and more integrated platforms became much more visible.

The geographic spread is broad, with studies from Asia, Europe, Africa, North America, and South America. Even so, the distribution of study types is uneven. Developed countries were more frequently represented in high-performance model development studies, while lower-cost prototypes were more common in developing countries. That matters because the field is not advancing along a single path; it is producing different kinds of solutions for different farm realities.

Study designs were also unevenly distributed. Prototype implementations dominated, followed by review papers, laboratory validations, and a much smaller number of commercial field evaluations. That is an important strength and limitation pattern. The field has demonstrated technical feasibility, but far fewer papers show that systems remain reliable over time, across seasons, or at scale. This is why the evidence is best understood as promising but still not yet fully established.

To provide an integrated comparison across the five identified technology domains, Table 1 summarizes their relative maturity, reported performance, major implementation constraints, and indicative cost requirements.

Table 1. Comparative summary of the five smart poultry farming technology domains.

Technology Domain	Maturity Level	Typical Accuracy Range	Primary Constraints	Estimated Cost Range
Internet of Things Environmental Monitoring	High (Commercial-ready)	93.7–99%+	scalability, maintenance, and affordability in smallholder systems	Low–Moderate
Artificial Intelligence / Machine Learning	Moderate–High	86–96.4%	limited field validation, dataset bias, computational demand	Moderate
Computer Vision	Moderate–High	85–97.8%	occlusion, stocking density effects, and large data requirements	Moderate–High
Acoustic Monitoring	Moderate	91.1–96.0%	farm noise interference, lack of standardized datasets	Low–Moderate
Robotics & Big Data Integration	Low–Moderate (Prototype-dominant)	87–100%*	high cost, integration complexity, and limited commercial deployment	High

**Higher reported accuracy often reflects task-specific performance under controlled or pilot conditions. Note: Cost categories are qualitative estimates based on the hardware, software, infrastructure, and maintenance requirements reported in the reviewed studies. "Low" indicates minimal investment, "Moderate" indicates intermediate resource requirements, and "High" indicates substantial investment in advanced technologies or infrastructure. These categories are relative and do not represent fixed monetary values.*

While many studies reported high performance metrics, including classification accuracies exceeding 90%, the methodological quality of the evidence varied considerably. Several studies were conducted under controlled laboratory conditions using limited datasets or prototype systems, whereas fewer studies reported long-term field validation in commercial poultry environments. Consequently, reported performance values should be interpreted with caution, as laboratory-based evaluation may not fully reflect operational performance under real-world production conditions. Technologies supported by the large datasets, external validation procedures, and commercial-scale implementation provide stronger evidence for practical adoption than early-stage proof-of-concept studies.

3.2 IoT-Based Environmental Monitoring and Control

The findings indicate that IoT-based environmental monitoring is the most widely studied and most commonly implemented technological domain in smart poultry farming. Chang and Tu (2023) and Liu et al. (2024) demonstrated that most studies published between 2020 and 2024 employed sensor networks to continuously monitor poultry house environmental conditions. Across these studies, temperature, relative humidity, and NH3 concentration were consistently identified as the most critical parameters due to their direct and well-established effects on broiler growth, respiratory health, and mortality rates (Lashari et al., 2023).

In terms of system architecture, a consistent hardware pattern was observed across studies. Orakwue et al. (2022) and Malini et al. (2023) reported widespread use of low-cost microcontrollers, particularly Arduino, ESP32, Raspberry Pi, and ESP8266 platforms. These devices were commonly integrated with DHT11 or DHT22 sensors for temperature and humidity monitoring and MQ135 or MQ7 sensors for gas detection (Nalendra & Waspada, 2025). While this relatively standardized hardware framework facilitated cross-study comparability, differences in system configuration and deployment design contributed to measurable performance variation. For example, Lashari et al (2023) reported temperature regulation within the target range of 32-34°C, with data accuracy exceeding 99% during a 500-day field deployment, demonstrating strong long-term reliability under commercial conditions. In contrast, Akinwumi et al (2024) reported 93.7% real-time accuracy with a 2-second transmission delay in a multi-objective IoT prototype, illustrating the performance trade-offs often associated with early-stage systems.

A major methodological distinction across studies involved system scalability. Some studies integrated IoT platforms with machine learning models to improve predictive decision-making. For instance, Fahrurrozi et al (2024) combined environmental sensor data with a Random Forest classifier, achieving 96.665% accuracy in poultry house condition classification. However, most prototype-level systems did not adequately address large-scale deployment challenges, including network scalability, maintenance complexity, and multi-sensor installation costs, limitations also emphasized by Ambafi et al (2025). In low-resource contexts such as Tanzania, Lufyagila et al (2021) reported 43% of smallholder farmers did not adopt available IoT systems primarily due to cost constraints, highlighting affordability as a major barrier to equitable technology adoption.

Studies published after 2023 increasingly incorporated edge-computing architectures to reduce data transmission requirements and support local decision-making. This shift was primarily driven by the need to reduce data transmission latency and support real-time decision-making in environments with unstable internet connectivity (Vijay et al., 2023). For example, Jebari et al (2023) developed a modular edge-AI-IoT platform capable of detecting harmful gas concentrations locally, while Eshilama et al (2025) introduced a hybrid sleep-scheduling algorithm that significantly improved IoT sensor energy efficiency. Compared with earlier studies (2020-2022), which largely depended on continuous cloud connectivity.

3.3 Artificial Intelligence and Machine Learning for Disease Detection and Health Management

Disease detection and health monitoring represent the second major focus area in the reviewed literature and the domain in which the most rapid methodological advancement has been observed. Studies published between 2020 and 2021 primarily discussed the potential role of AI and Internet of Things in disease prevention and health management, although most did not introduce new experimental models (Singh et al, 2020). From 2022 onward, however, a substantial increase in experimental studies was observed, with researchers increasingly applying convolutional neural networks (CNNs), transfer learning, and ensemble approaches to detect specific and health-related abnormalities using image, thermal, and behavioral datasets (Shwetha et al, 2024).

Among deep learning approaches, the YOLO (You Only Look Once) family of object detection algorithms emerged as one of the most widely adopted methods. By 2024-2025, YOLOv7, YOLOv8, and YOLOv11 had been applied to identify abnormal fecal patterns, bumblefoot, woody breast syndrome, and general health abnormalities using both RGB and thermal imaging. For example, Natho et al (2025) trained a YOLOv11 model using 1,716 augmented images of Thai farm chickens and achieved a precision o.964, a recall of 0.938, and a mean average precision (mAP) of 0.963, demonstrating that high diagnostic performance can be achieved even with relatively small datasets. Similarly, Xu and Chang (2024) integrated YOLOv7 with long short-term memory (LSTM) networks to simultaneously analyze fecal images and chicken vocalizations, achieving 86% mAP for sound-based disease detection and 83% accuracy for classifying three diseases using fecal images. These multimodal approaches highlight the growing potential of combining visual and acoustic data for more comprehensive health monitoring; however, their application under commercial farm conditions remains limited.

A key methodological distinction emerged between studies using traditional machine learning models and those employing deep learning approaches. Ali et al (2024) applied several supervised machine learning models, including Random Forest, Decision Tree, K-Nearest Neighbors, Support Vector Machine (SVM), and Naïve Bayes, to structured poultry house environmental data, with the Decision Tree Model achieving the highest classification accuracy for environmental control decisions. In contrast, Natsir et al (2025) reported that CNN-based architectures, particularly YOLOv8, consistently outperformed traditional machine learning methods in image-based disease detection tasks, with reported accuracies exceeding 90% across multiple studies. This contrast reflects the differing strengths of these approaches: traditional machine learning remains computationally efficient and highly effective for structured sensor datasets, whereas deep learning performs better with unstructured data such as images and audio. Notably, studies published between 2020 and 2022 relied more heavily on traditional machine learning due to lower computational requirements, while studies from 2023 onwards show a clear transition toward deep learning, driven by decreasing hardware costs and increasing availability of large, annotated datasets (Erike et al, 2025).

Disease outbreak prediction using ICT-generated big data is still a developing area that has not been thoroughly explored. Society and Woo (2023) created a disease occurrence prediction model (DOPM) for broiler farms in South Korea. This model used data on feed intake and water consumption. It showed that lasting drops in feed intake could act as a reliable early warning signal, or "golden time," for disease onset. This allows for earlier intervention compared to traditional methods that rely on mortality rates. Similarly, He et al. (2022) looked at various symptom-monitoring technologies like body temperature tracking, vocalization analysis, and behavioral monitoring. They found that these systems perform better than manual inspection but are still not well integrated into comprehensive early warning platforms.

3.4 Computer Vision and Behavioral Analysis

Computer vision is a quickly growing area in smart poultry farming. Its uses include identifying individual birds, estimating flock density, recognizing activity, analyzing posture, estimating body weight, and monitoring welfare indicators and abnormal behaviors (Aziz et al., 2020; Li et al., 2021; Campbell et al., 2024). Over time, these applications have become more advanced. Early studies published between 2020 and 2021 mostly focused on basic object detection tasks. In contrast, studies from 2024 to 2026 increasingly used advanced spatiotemporal analysis methods. These methods can capture both movement dynamics and behavioral changes over time with greater accuracy.

The reviewed literature indicates that YOLO-based and related computer vision models provide robust baseline performance for individual bird detection and tracking. Čakić et al. (2023) developed edge artificial intelligence computer vision models utilizing Faster R-CNN architectures, trained on high-performance computing resources, and achieved an average precision (AP) of 85% for object detection. These models were subsequently deployed on edge devices in real-world poultry farm environments. Similarly, Neethirajan (2022) introduced the ChickTrack framework, which integrates YOLOv5 with Kalman filtering for multi-chicken tracking. In addition to detection, behavioral classification systems demonstrated high accuracy. Mohialdin et al. (2023) applied Light Gradient Boosting to behavioral datasets, achieving 94.7% accuracy in identifying behaviors such as feeding, walking, and sleeping. Elbarrany et al. (2023) further incorporated convolutional neural network (CNN)-based heatmap analysis and reported 96.43% accuracy in detecting abnormal behaviors.

Despite these advances, a consistent methodological limitation across behavioral analysis studies was occlusion, where birds become partially or fully obscured by equipment, flockmates, or structural components of the housing environment. Merenda et al. (2025) identified occlusion as a major factor reducing both detection and tracking accuracy. Similarly, Malini et al. (2024) reported strong performance for feeding (0.895) and drinking (0.90) behavior detection, but substantially lower accuracy for active (0.545) and inactive (0.505) states, primarily due to identity loss during prolonged tracking. These findings suggest that current systems perform well for clearly observable and discrete behaviors but remain less reliable for subtle, continuous, or temporally complex activities.

To address these limitations, more recent studies have increasingly adopted spatiotemporal deep learning approaches. Wang et al. (2025), for example, developed the BBRS system integrating a 3D-ResNet50-TSAM architecture for advanced temporal feature extraction and achieved 97.84% behavior recognition accuracy across five behavioral categories. Although this represents one of the highest-performing systems identified in this review, it was evaluated under a relatively low stocking density of 7–8 birds/m². Commercial broiler production systems frequently operate at substantially higher stocking densities, often exceeding 10–15 birds/m² depending on production practices and regional regulations. Consequently, the reported performance may not be directly generalizable to more densely populated commercial environments where bird occlusion, movement overlap, and environmental complexity are greater.

3.5 Acoustic Monitoring and Vocalization Analysis

Monitoring sounds of poultry has developed into a vital non-invasive tool for analyzing the well-being and welfare of poultry. In 2022 and after, there was a substantial increase in studies on this issue, and between 2025 and 2026, it became one of the rapidly growing fields of smart poultry farming research (Manikandan & Neethirajan, 2025). The scientific foundation for this methodology is solid because vocalization by chickens provides significant data concerning their state of health, emotions, reaction to stress, feeding, and social interactions.

The same methodological framework was used in the majority of acoustic monitoring systems presented in the literature. Namely, such systems were generally comprised of three main steps: (1) acquisition of acoustic signals through microphones located at certain positions, (2) extraction of various acoustic characteristics, including Mel-Frequency Cepstral Coefficients (MFCCs), spectrograms, and other spectral descriptors, and (3) classification via machine or deep learning techniques (Manikandan & Neethirajan, 2025). For instance, Bhandekar et al. (2023) used an SVM classifier based on MFCC features that classified abnormal chicken farm sounds with 95.66% accuracy; the system was updated once every 30 minutes for near-real-time detection. In addition, De Carvalho Soster et al. (2025) developed a 12-layer Convolutional Neural Network (CNN) classifier that recognized four vocalizations in Ross 308 broilers, namely pleasure sounds, distress sounds, short peeping sounds, and warble sounds; 2,123 examples of those vocalizations were used, and the overall balanced accuracy was 91.1%.

3.6 Robotics, Automation, and Big Data Integration

Results demonstrate that the most integrated and systemic level of development in intelligent poultry farming is related to robotics and the complete automation of farms (Sajid et al., 2024). Specifically, various studies discussed the utilization of robots for such activities as egg collection in both free-range and commercial systems, automatic feeding and watering, patrols for environmental conditions, activities associated with controlling diseases, and litter management (Park et al., 2022). This demonstrates that apart from simply gathering information about farms, the implementation of robotics allows performing actual operations in agriculture as well. In particular, Chang et al. (2020) proposed a mobile robot for egg collection in free-range chicken farming capable of egg recognition and collection under different outdoor conditions. As a result, an efficiency level of 94.7% to 97.6% was obtained during experiments performed on an outdoor area of 5 m × 5 m. In a more general study focused on identifying the key application areas of poultry robotics, Özentürk et al. (2024) considered such fields as environmental monitoring, disease control, floor egg collection, and welfare evaluation but pointed out that certain knowledge gaps remain.

Big Data and predictive analytics play a critical role in providing the overarching digital ecosystem for such smart systems. As Franzo et al. (2023) noted, there has been a significant transformation brought by big data in the poultry sector, with the use of visual data, acoustic data, wearable sensors, pathogen genomic data, and population data allowing for better prediction and decision-making. In practical terms, Liu et al. (2024) created an intelligent service platform and found it to be very reliable during commercial usage. During a 500-day experiment within a commercial poultry barn, the system was able to sustain more than 87% of data integrity, while temperature, humidity, and CO_2 measurements reached over 99% validity. Thus, it has become possible to implement big data systems on multiple farms using IoT technology.

A consistent finding across studies on robotics and big data integration was that multimodal systems outperform single-source systems by generating more detailed, reliable, and context-aware insights (Panagi et al., 2025). These systems typically combine environmental sensors, cameras, microphones, wearable devices, and production records into unified analytical platforms. A notable example is the PoultryFI platform, which integrated six AI-driven modules, including audio-visual monitoring, automated egg counting, production forecasting, and environmental recommendation systems. During field testing, the platform achieved 100% accuracy in egg counting using a Raspberry Pi 5 edge device, while also demonstrating effective anomaly detection and short-term production forecasting.

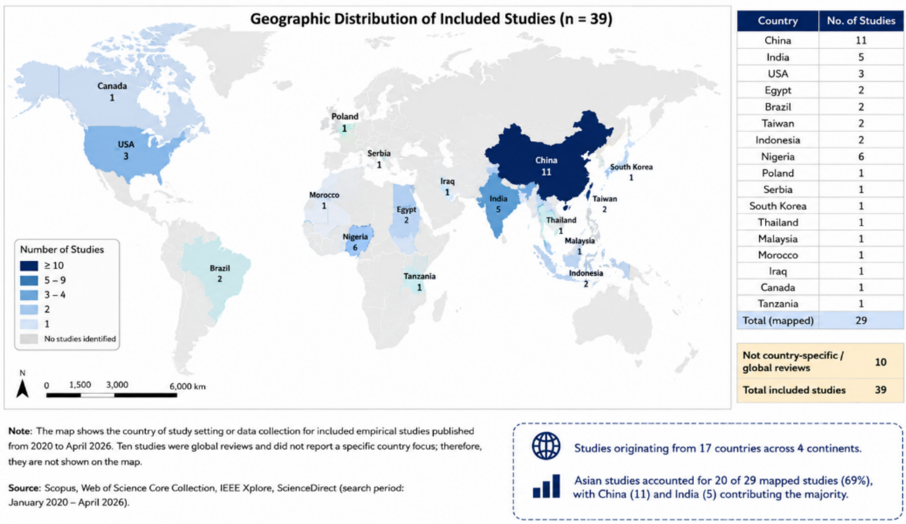

Figure 2. Global geographic distribution of included studies (2020–2026).

4. Discussion

The findings of this systematic review indicate substantial technological progress in smart poultry farming and demonstrate the potential of IoT, artificial intelligence, computer vision, acoustic monitoring, and multimodal systems to improve farm management. Across the reviewed studies, automated technologies frequently achieved high performance under experimental and pilot-scale conditions and often outperformed conventional monitoring approaches in terms of speed, consistency, and data resolution. However, the overall strength of evidence remains uneven. While some technologies have progressed beyond proof-of-concept stages and undergone commercial-scale testing, many reported systems remain at the prototype or pilot level and lack extensive long-term validation across the technical feasibility of smart poultry systems, but provide more limited evidence regarding their large-scale commercial effectiveness, economic sustainability and long-term welfare impacts.

This shift is highly compatible with the main tenet of Precision Livestock Farming, which revolves around the necessity to monitor each individual animal so that management can be more efficient and humane compared to the conventional method of observing groups of animals. Overall, the discussed findings appear to favor the model proposed by PLF proponents. Still, the effective operation of these systems does not depend only on the technology itself but also requires farmers to understand and react to the information provided by the system. Given the inequalities in access to infrastructure and finances between production systems, it appears likely that the benefits of this innovative approach may become accessible unequally to all producers.

Amongst some of the issues that arise from the literature is one regarding whether or not intelligent poultry farming actually benefits animals or merely acts as a way to produce at a high density and make it appear as though welfare improvements are being made through the use of technology. The evidence that exists currently does not adequately answer this question yet. What has been seen so far are mostly short-term, experimental, or prototype studies with few examples in commercial welfare settings.

4.1 Similarities, Differences, and Contradictions Across Studies

Several consistent patterns emerged across the reviewed literature. Most notably, monitoring of temperature, humidity, and ammonia levels was repeatedly identified as a foundational requirement of smart poultry farming systems, reflecting the central role of environmental control in maintaining poultry health and productivity (Chang & Tu, 2023).

At the same time, important methodological differences and contradictions were observed. One major source of variation involved dataset size and diversity. Some studies were based on fewer than 100 images or recordings, whereas others used datasets containing hundreds of thousands of samples. This inconsistency directly influenced reported accuracy values and limited the comparability of findings across studies (Li, 2025; Natho et al., 2025). Another significant difference involved the testing environment. Studies conducted under controlled laboratory conditions generally reported substantially higher performance than those implemented under real farm conditions, highlighting a persistent laboratory-to-field performance gap across multiple technology domains.

Regional differences in system design were also evident. Studies from Asia and Africa more frequently emphasized low-cost, adaptable prototype systems designed for resource-constrained environments, whereas studies from Europe and North America more commonly focused on advanced, high-performance platforms supported by larger datasets and greater hardware investment. These differences reflect variation in production scale, regulatory requirements, infrastructure availability, and farmer digital literacy. Collectively, they suggest that smart poultry farming technologies cannot be universally standardized and must instead be adapted to local production realities.

4.2 Interpretation of Reported Performance Metrics

Although many studies reported high performance values, including classification accuracies exceeding 90%, these metrics should be interpreted with caution. Direct comparison across technologies was limited by substantial methodological heterogeneity among studies. Differences in dataset size, poultry species, production systems, environmental conditions, outcome definition, and validation procedures make performance metrics inherently context-dependent.

For example, some computer vision studies were trained and tested using highly curated image datasets collected under controlled laboratory conditions, whereas others were evaluated in commercial poultry houses characterized by variable lighting, stocking density, and environmental complexity. Similarly, acoustic monitoring studies differed in microphone placement, background noise levels, and vocalization categories, while IoT-based monitoring systems often measured different environmental parameters and operated under distinct deployment conditions.

Consequently, higher reported accuracy does not necessarily indicate superior real-world performance. Technologies validated using large datasets, independent test sets, or commercial farm deployments provide stronger evidence than systems evaluated solely under experimental conditions. Therefore, the accuracy values reported throughout this review should be interpreted as indicators of technical potential rather than definitive measures of comparative effectiveness.

Evidence synthesis revealed that only a small proportion of included studies involved long-term commercial validation, whereas the majority were conducted under experimental, pilot-scale, or controlled conditions. This suggests that many smart poultry technologies remain in transitional stages between proof-of-concept development and large-scale commercial deployment. A comprehensive summary of the included studies, including country, technology domain, study design, dataset characteristics, validation setting, principal findings, and evidence level, is provided in Supplementary Table S1

4.3 Research Gaps and Limitations

Despite the rapid growth and clear relevance of this field, five major gaps continue to limit the full potential of smart poultry farming technologies.

First, the most significant gap is the lack of long-term, large-scale field validation. Although many studies demonstrate strong performance under laboratory or pilot conditions, relatively few have assessed system reliability, maintenance requirements, and productivity outcomes over extended production cycles in commercial settings. Among the reviewed literature, only three studies reported field implementations lasting beyond a single production cycle (Lashari et al., 2023; Liu et al., 2024; Huang 2024), and none evaluated multi-year performance across multiple farms while simultaneously measuring animal welfare outcomes. This represents a major evidence limitation.

Second, a substantial equity gap remains due to the underrepresentation of smallholder, backyard, and low-resource production systems. Most advanced smart poultry technologies have been developed within large-scale commercial environments that already possess strong infrastructure and financial capacity. This limits the relevance of current innovations for the majority of global poultry producers operating under constrained conditions.

Third, the field lacks standardized datasets, evaluation protocols, and performance metrics. This significantly reduces reproducibility and limits cross-study comparability. As highlighted by Li (2025) and Manikandan and Neethirajan (2025), the absence of shared open-access benchmark datasets remains a major barrier to cumulative scientific progress.

Fourth, multimodal sensor fusion, the integration of environmental, visual, acoustic, and wearable data into unified analytical systems, remains largely conceptual rather than widely implemented. Although frequently identified as the future direction of smart poultry farming (Franzo et al., 2023; Natsir et al., 2025), most existing systems still rely on only one or two data sources. Developing efficient real-time fusion architectures, particularly for edge computing environments, remains an important unresolved challenge.

Finally, the social, ethical, and regulatory dimensions of smart poultry farming remain insufficiently addressed. Issues such as welfare risks associated with technology-driven intensification, algorithmic decision transparency, data ownership, and farmer dependency on automated systems have received limited attention. Without stronger ethical and governance frameworks, rapid technological adoption may outpace responsible implementation.

4.4 Limitation of this Review

Although this systematic review provides a comprehensive synthesis of recent advances in smart poultry farming, several limitations should be acknowledged. First, the review included only peer-reviewed articles published in English, which may have introduced language bias by excluding relevant studies published in other languages. Second, because published studies reporting positive or significant findings are more likely to appear in indexed databases, the review may be influenced by publication bias, potentially overestimating the reported effectiveness of smart poultry technologies. Third, the exclusion of non-peer-reviewed literature, including conference proceedings, technical reports, and industry white papers, may have limited the inclusion of emerging technologies that have not yet entered formal academic publication. Fourth, substantial methodological heterogeneity across included studies—including differences in study design, datasets, evaluation metrics, and experimental settings—prevented formal meta-analysis and limited direct quantitative comparison across technologies. Finally, because this review focused on studies published between 2020 and 2026, earlier foundational developments in precision livestock farming were intentionally excluded to prioritize recent advances, which may limit historical contextualization. Despite these constraints, the review provides a robust and current synthesis of the field and identifies critical directions for future research.

4.5 Key Findings

Table 2. Key findings of the review.

Domain	Key Finding
IoT Environmental Monitoring	Most mature domain; strong commercial readiness with >93% reported accuracy.
AI/ML Disease Detection	Fastest-growing area; deep learning models consistently outperformed traditional methods.
Computer Vision	Highly accurate for detection and behavior monitoring but challenged by occlusion and dense flock environments.
Acoustic Monitoring	Emerging high-potential tool; real-farm studies show performance can exceed human experts.
Robotics & Big Data	Most integrated systems are still largely at prototype or pilot scale.
Cross-cutting Challenge	Limited long-term field validation, lack of standardized datasets, and weak smallholder inclusion.
Overall Conclusion	Smart poultry technologies are technically promising but require stronger real-world validation and inclusive implementation strategies.

Evidence synthesis revealed that only a small proportion of included studies involved long-term commercial validation, whereas the majority were conducted under experimental, pilot-scale, or controlled conditions. This suggests that many smart poultry technologies remain in transitional stages between proof-of-concept development and large-scale commercial deployment.

5. Conclusion

This systematic review evaluated the current state of smart poultry farming by synthesizing evidence from thirty-nine (39) peer-reviewed studies published between 2020 and 2026 under PRISMA 2020 guidelines. The findings show that technologies such as Internet of Things, Artificial Intelligence, computer vision, acoustic monitoring, and robotics are rapidly transforming poultry production from reactive management toward predictive and precision-based systems, improving efficiency, scalability, and welfare monitoring. The main contribution of this review is its integrated cross-theme synthesis, which distinguishes field-ready technologies from emerging prototypes and highlights persistent gaps between laboratory performance and commercial implementation. These findings strengthen the theoretical foundation of Precision Livestock Farming while offering practical guidance for researchers, producers, and policymakers seeking scalable and context-appropriate solutions. However, limited long-term field validation, lack of standardized datasets, and underrepresentation of smallholder systems remain important constraints. Future research should prioritize multi-farm longitudinal studies, multimodal system integration, standardized evaluation frameworks, and stronger ethical and policy frameworks to ensure that smart poultry farming develops in a sustainable, inclusive, and responsible manner.

Based on the findings of this review, several recommendations are proposed to support the sustainable development of smart poultry farming. First, future research should prioritize large-scale, long-term field validation using standardized animal welfare and productivity indicators to strengthen evidence for commercial adoption. Second, the development of open and standardized datasets is needed to improve reproducibility and comparability across studies. Third, greater attention should be given to designing affordable, user-friendly, and offline-capable technologies suitable for smallholder and resource-limited farming systems. Fourth, advancing multimodal systems that integrate environmental, visual, acoustic, and wearable data should remain a key technical priority. Given the current limitations of short-term experimental studies and limited smallholder representation, future work should also address broader ethical, regulatory, and governance issues, including responsible automation and animal welfare protection. Ultimately, the success of Precision Livestock Farming will depend not only on technological innovation but on ensuring that these systems are inclusive, practical, and sustainable across diverse production contexts.

Acknowledgment

The authors would like to thank the colleagues and institutions who provided guidance, feedback, and support throughout the conduct of this research and the preparation of this manuscript. Any remaining errors or omissions are the sole responsibility of the authors.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

References

Akinwumi, A. O., Onibonoje, M. O., & Yusuff, A. S. (2024). Development of a sustainable Multi-Objective approach to poultry management system with IoT-Based environmental monitoring. Authorea. https://doi.org/10.22541/au.170995062.20191201/v1

Ali, M., Imran, M., Baig, M. S., Shah, A., Ullah, S. S., Alroobaea, R., & Iqbal, J. (2024). Intelligent control shed poultry farm system incorporating with machine learning. *IEEE Access*, *12*, 58168-58180. https://doi.org/10.1109/access.2024.3391822

Ambafi, J., Muhammad, Y., Ahmad, A., Ohize, H., Dauda, U., & Musa, J. (2025). A review on development of an IoT-Based system for enhancing yield in poultry Farming. *Confluence Journal of Science and Technology, 2*(1), 116. https://doi.org/10.5455/cujostech.250414

Aziz, N. S. N. A., Daud, S. M., Dziyauddin, R. A., Adam, M. Z., & Azizan, A. (2020). A review on Computer vision Technology for Monitoring Poultry Farm—Application, hardware, and software. *IEEE Access, 9*, 12431–12445. https://doi.org/10.1109/access.2020.3047818

Bhandekar, A., Udutalapally, V., & Das, D. (2023). Acoustic Based Chicken Health Monitoring in Smart Poultry Farms. IEEE International Symposium on Smart *Electronic Systems (iSES),* 224–229. https://doi.org/10.1109/ises58672.2023.00054

Cakic, S., Popovic, T., Krco, S., Nedic, D., Babic, D., & Jovovic, I. (2023). Developing Edge AI computer vision for smart poultry farms using deep learning and HPC. *Sensors, 23*(6), 3002. https://doi.org/10.3390/s23063002

Campbell, M., Miller, P., Díaz-Chito, K., Hong, X., McLaughlin, N., Parvinzamir, F., Del Rincón, J. M., & O'Connell, N. (2024). A computer vision approach to monitor activity in commercial broiler chickens using trajectory-based clustering analysis. *Computers and Electronics in Agriculture,* 217, 108591. https://doi.org/10.1016/j.compag.2023.108591

Chang, C., Xie, B., & Wang, C. (2020). Visual guidance and egg collection scheme for a smart poultry robot for Free-Range farms. *Sensors, 20*(22), 6624. https://doi.org/10.3390/s20226624

Chang, Y., & Tu, L. (2023). Use of IoT sensors to build an intelligent monitoring and control system for poultry house environment. Sensors and Materials, 35(12), 3997. https://doi.org/10.18494/sam4582

De Carvalho Soster, P., Grzywalski, T., Hou, Y., Thomas, P., Dedeurwaerder, A., De Gussem, M., Tuyttens, F., Devos, P., Botteldooren, D., & Antonissen, G. (2025). Automated detection of broiler vocalizations a machine learning approach for broiler chicken vocalization monitoring. *Poultry Science, 104*(5), 104962. https://doi.org/10.1016/j.psj.2025.104962

Elbarrany, A. M., Mohialdin, A., & Atia, A. (2023). Abnormal Behavior Analysis for Surveillance in Poultry Farms using Deep Learning. *Intelligent Methods, Systems, and Applications (IMSA),* 56–61. https://doi.org/10.1109/imsa58542.2023.10217676

Erike, A., Ikerionwu, C., Azubogu, A., & Obodoagwu, V. (2025). Is AI for illiterate farmers? A systematic literature review of AI and machine learning applications and challenges for precision agriculture. *Discover Artificial Intelligence, 5*(1). https://doi.org/10.1007/s44163-025-00457-9

Eshilama, D. A., Udofia, K. M., & Udofia, K. M. (2025). Hybrid Sleep Scheduling for Energy-Efficient IoT Sensor Networks in Smart Poultry Monitoring. *Asian Journal of Research in Computer Science*, *18*(11), 107-123. https://hal.science/hal-05358517/

Fahrurrozi, I., Wahyono, W., Sari, Y., Sari, A. K., Usuman, I., & Ariyadi, B. (2024). Integrating random forest model and internet of things-based sensor for smart poultry farm monitoring system. *Indonesian Journal of Electrical Engineering and Computer Science, 33*(2), 1283. https://doi.org/10.11591/ijeecs.v33.i2.pp1283-1292

Franzo, G., Legnardi, M., Faustini, G., Tucciarone, C. M., & Cecchinato, M. (2023). When everything becomes bigger: big data for big poultry production. *Animals, 13*(11), 1804. https://doi.org/10.3390/ani13111804

He, P., Chen, Z., Yu, H., Hayat, K., He, Y., Pan, J., & Lin, H. (2022). Research progress in the early warning of chicken diseases by monitoring clinical symptoms. *Applied Sciences, 12*(11), 5601. https://doi.org/10.3390/app12115601

Huang, J. (2024). SmartEars: An intelligent method for monitoring poultry respiratory illnesses based on audio signals [Dataset]. *In Mendeley Data*. https://doi.org/10.17632/dy6gtvt4mk.1

Shomina, N., & Beltrán-Alcrudo, D. (2025). Improving poultry health and productivity. https://doi.org/10.4060/cd7901en

Jebari, H., Mechkouri, M. H., Rekiek, S., & Reklaoui, K. (2023). Poultry-Edge-AI-IoT system for Real-Time monitoring and Predicting by using artificial intelligence. *International Journal of Interactive Mobile Technologies (iJIM), 17*(12), 149–170. https://doi.org/10.3991/ijim.v17i12.38095

Lashari, M. H., Karim, S., Alhussein, M., Hoshu, A. A., Aurangzeb, K., & Anwar, M. S. (2023). Internet of Things-based sustainable environment management for large indoor facilities. *PeerJ Computer Science, 9*, e1623. https://doi.org/10.7717/peerj-cs.1623

Li, G. (2025). A survey of open-access datasets for computer vision in precision poultry farming. *Poultry Science, 104*(2), 104784. https://doi.org/10.1016/j.psj.2025.104784

Li, G., Huang, Y., Chen, Z., Chesser, G. D., Purswell, J. L., Linhoss, J., & Zhao, Y. (2021). Practices and Applications of Convolutional Neural Network-Based Computer Vision Systems in Animal Farming: A review. *Sensors, 21*(4), 1492. https://doi.org/10.3390/s21041492

Liu, M., Chen, H., Zhou, Z., Du, X., Zhao, Y., Ji, H., & Teng, G. (2024). Development of an intelligent service platform for a poultry house facility environment based on the Internet of Things. *Agriculture, 14*(8), 1277. https://doi.org/10.3390/agriculture14081277

Lufyagila, B., Machuve, D., & Clemen, T. (2022). IoT-powered system for environmental conditions monitoring in poultry house: A case of Tanzania. *African Journal of Science, Technology, Innovation and Development, 14*(4), 1020-1031. https://hdl.handle.net/10520/ejc-aa_ajstid_v14_i4_a1020

Malini, T., Aswath, D. L., Abhishek, R., Kirubhakaran, R., & Anandhamurugan, S. (2023, March). IoT based smart poultry farm monitoring. In *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)* (Vol. 1, pp. 13-18). IEEE. https://doi.org/10.1109/icaccs57279.2023.10112870

Manikandan, V., & Neethirajan, S. (2025). AI-driven bioacoustics in poultry farming: A critical systematic review on vocalization analysis for stress and disease detection. *Preprint*. https://doi.org/10.20944/preprints202505.1369.v1

Merenda, V. R., Bodempudi, V. U., Pairis-Garcia, M. D., & Li, G. (2024). Development and validation of machine-learning models for monitoring individual behaviors in group-housed broiler chickens. *Poultry Science, 103*(12), 104374. https://doi.org/10.1016/j.psj.2024.104374

Mohialdin, A. M., Elbarrany, A. M., & Atia, A. (2023). Chicken behavior Analysis for surveillance in poultry farms. *International Journal of Advanced Computer Science and Applications, 14*(3). https://doi.org/10.14569/ijacsa.2023.01403106

Nalendra, A. K., & Waspada, H. P. (2025). Smart Poultry Farming: a Mobile-Based IoT system for Real-Time broiler monitoring and management. *International Journal of Electronics and Communications Systems, 5*(1), 81–91. https://doi.org/10.24042/ijecs.v5i1.27622

Natho, P., Boonying, S., Bonguleaum, P., Tantidontanet, N., & Chamuthai, L. (2025). An enhanced machine vision system for smart poultry farms using deep learning. *Smart Agricultural Technology, 12,* 101083. https://doi.org/10.1016/j.atech.2025.101083

Natsir, M. H., Mahmudy, W. F., Tono, M., & Nuningtyas, Y. F. (2025). Advancements in artificial intelligence and machine learning for poultry farming: Applications, challenges, and future prospects. *Smart Agricultural Technology, 12*, 101307. https://doi.org/10.1016/j.atech.2025.101307

Neethirajan, S. (2022). ChickTrack – A quantitative tracking tool for measuring chicken activity. *Measurement, 191,* 110819. https://doi.org/10.1016/j.measurement.2022.110819

Ojo, R. O., Ajayi, A. O., Owolabi, H. A., Oyedele, L. O., & Akanbi, L. A. (2022). Internet of Things and Machine Learning techniques in poultry health and welfare management: A systematic literature review. *Computers and Electronics in Agriculture, 200*, 107266. https://doi.org/10.1016/j.compag.2022.107266

Olejnik, K., Popiela, E., & Opaliński, S. (2022). Emerging precision management methods in poultry sector. *Agriculture, 12*(5), 718. https://doi.org/10.3390/agriculture12050718

Orakwue, S. I., Al-Khafaji, H. M. R., & Chabuk, M. Z. (2022). IoT based smart monitoring system for efficient poultry farming. *Webology, 19*(1), 4105–4112. https://doi.org/10.14704/web/v19i1/web19270

Özentürk, U., Chen, Z., Jamone, L., & Versace, E. (2024). Robotics for poultry farming: Challenges and opportunities. *Computers and Electronics in Agriculture, 226,* 109411. https://doi.org/10.1016/j.compag.2024.109411

Panagi, P., Karatsiolis, S., Mosphilis, K., Hadjisavvas, N., Kamilaris, A., Nicolaou, N., ... & Vassiliades, V. (2025). Poultry Farm Intelligence: An Integrated Multi-Sensor AI Platform for Enhanced Welfare and Productivity. *arXiv preprint arXiv:2510.15757*. https://doi.org/10.2139/ssrn.5342267

Park, M., Britton, D., Daley, W., McMurray, G., Navaei, M., Samoylov, A., Usher, C., & Xu, J. (2022). Artificial intelligence, sensors, robots, and transportation systems drive an innovative future for poultry broiler and breeder management. Animal Frontiers, 12(2), 40–48. https://doi.org/10.1093/af/vfac001

Sajid, M. A., Akhtar, I., Rauf, U., Hafeez, S., Tahir, Y., Abdullah, M., Ather, N., Yasin, N., & Asghar, R. (2024). Smart Sensors and Robotics in Poultry Farming; Transforming Operational efficiency A review. *Scholars Journal of Agriculture and Veterinary Sciences, 11*(07), 133–145. https://doi.org/10.36347/sjavs.2024.v11i07.003

Singh, M., Kumar, R., Tandon, D., Sood, P., & Sharma, M. (2020). Artificial intelligence and iot based monitoring of poultry health: A review. In *2020 IEEE international conference on communication, networks and satellite (Comnetsat)* (pp. 50-54). IEEE. https://doi.org/10.1109/comnetsat50391.2020.9328930

Society, K. I. T. C., & Woo, Y. (2023). A study on the development of a disease occurrence Prediction Model (DOPM) based on big data analysis of ICT equipment in broiler farms. *Korea Industrial Technology Convergence Society, 28*(3), 29–45. https://doi.org/10.29279/jitr.2023.28.3.29

Shwetha, V., Maddodi, B. S., Laxmi, V., Kumar, A., & Shrivastava, S. (2024). Latest trend and challenges in machine learning–and deep learning–based computational techniques in poultry health and disease management: A review. *Journal of Computer Networks and Communications*, *2024*. https://www.researchgate.net/profile/Shwetha-V/publication/384967444_Latest_Trend_and_Challenges_in_Machine_Learning-_and_Deep_Learning-Based_Computational_Techniques_in_Poultry_Health_and_Disease_Management_A_Review/links/670fbb0d035917754c04e1ac/Latest-Trend-and-Challenges-in-Machine-Learning-and-Deep-Learning-Based-Computational-Techniques-in-Poultry-Health-and-Disease-Management-A-Review.pdf

Vijay, A., Garg, T., Goyal, V., Yadav, A., & Mukherjee, R. (2023, January). A low-cost edge-iot based smart poultry farm. In *2023 15th International Conference on COMmunication Systems & NETworkS (COMSNETS)* (pp. 397-399). IEEE. https://doi.org/10.1109/comsnets56262.2023.10041317

Wang, J., Du, Z., Wen, B., Wu, Z., & Lin, X. (2025). EML-SlowFast: A behavior recognition model for lion-head goose. *Poultry Science, 104*(8), 105221. https://doi.org/10.1016/j.psj.2025.105221

Xu, R. Y., & Chang, C. L. (2024, April). Deep learning-based poultry health diagnosis: detecting abnormal feces and analyzing vocalizations. In *2024 10th international conference on applied system innovation (ICASI)* (pp. 55-57). IEEE. https://doi.org/10.1109/icasi60819.2024.10547723

Author Contributions: Cahanap, J.; Study design, method conception, data collection, data analysis, and manuscript writing. Abalde, L.; Data validation, visualization, critical review, and editing. Entana, R.; Funding acquisition, resource provision, and supervision. Sambulan, D.; Manuscript editing and funding acquisition.