

Digital Transformation of Poultry Farming Through Artificial Intelligence

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Abstract: The global poultry sector is under pressure to increase efficiency, sustainability, and animal welfare amid growing demand and resource constraints. Artificial Intelligence (AI) has emerged as a key enabler of digital transformation in poultry farming, yet evidence on practical adoption remains fragmented, especially for smallholder and UMKM contexts. **Objective:** This study systematically maps AI applications in poultry farming, classifies their functional domains and technological approaches, evaluates reported benefits and limitations, and identifies research gaps related to real-world implementation. **Method:** A PRISMA 2020-guided Systematic Literature Review (SLR) was conducted on 28 peer-reviewed, open-access, Scopus-indexed journal articles published between 2020 and 2025. Data were extracted on AI techniques, data modalities, application domains, implementation settings, and reported outcomes, then synthesized using thematic analysis. **Findings:** AI applications concentrate on disease detection and health monitoring, environmental control, behavior and welfare analysis, feed optimization, and productivity forecasting. Deep learning and computer vision dominate image/video-based tasks, while conventional machine learning supports multivariate prediction. Most studies report laboratory or pilot validation rather than full field deployment. Common barriers include high initial costs, limited digital literacy, infrastructure constraints (e.g., connectivity), and scarce localized datasets challenges that are particularly salient in developing-country settings. **Implications:** Adoption is most feasible through affordable, modular monitoring and decision-support solutions, supported by local dataset development, capacity building, and multi-stakeholder partnerships to translate pilots into sustained deployments. **Originality/Value:** This review integrates functional classification, technological mapping, and implementation maturity into a unified framework, offering an operational perspective on how AI can be scaled inclusively in poultry farming.

Keywords: Artificial Intelligence; Poultry Farming; Precision Livestock Farming; Smart Agriculture; Digital Transformation

INTRODUCTION

The poultry sector is a cornerstone of global food security because it supplies affordable animal protein with fast production cycles. Yet poultry operations are increasingly exposed to disease outbreaks, climate variability, volatile feed costs, and labor constraints pressures that heighten the need for tighter biosecurity, more reliable monitoring, and better decision-making at farm level (Fao, 2021; World, 2023). These

challenges have accelerated interest in digital approaches that can translate day-to-day farm signals into timely management actions rather than relying on manual observation alone.

This need is especially visible in Indonesia, where poultry production supports a wide base of micro-, small-, and medium-scale enterprises (UMKM). While large integrators can adopt advanced technologies, many UMKM farms still face uneven access to capital, infrastructure, and technical support, which limits their ability to implement data-driven management consistently (Indonesia, 2022; Wibowo & Utami, 2022). Consequently, the central practical question is not whether AI can improve poultry farming, but which AI functions are feasible and impactful under resource constraints.

Against this field reality, the first major strand of research develops AI within Precision Livestock Farming (PLF) architectures by combining sensors, connectivity, and analytics to enable continuous environmental and operational monitoring. Studies commonly propose IoT-based farm management systems and cloud-connected pipelines that integrate multi-sensor data to support anomaly detection and routine control of housing conditions (Huang & Yang, 2022; Mohammadrezaei et al., 2020; Neethirajan, 2020; Tran & Bui, 2020; Zhang et al., 2021). However, many reports emphasize technical feasibility while providing limited evidence on durability, maintenance burden, and cost-performance trade-offs across varied farm sizes and infrastructure conditions.

Building on these infrastructures, a second research stream concentrates on computer vision and audio analytics for health and welfare outcomes. Deep learning is frequently applied for disease-related early warning, posture and activity recognition, and image-based estimation tasks, illustrating the promise of automated detection when visual or acoustic cues can be captured reliably (Imran & Khan, 2022; Kim & Lee, 2023; Zhao et al., 2022; Zhuang & Shen, 2021). Even so, the literature repeatedly notes constraints that affect transfer from controlled datasets to real farms, including dependence on large labeled datasets, sensitivity to environmental noise and lighting, and limited generalizability across breeds and housing systems (Al-Qurashi & Tashkandi, 2021).

A third stream shifts from detection toward optimization and decision support, using predictive modeling and integrated platforms to inform feeding strategies, productivity forecasting, and management recommendations. Decision support systems and forecasting models are reported to improve planning, reduce waste, and strengthen operational control when paired with farm data streams and cloud computing (Kassab & ElBanna, 2022; Rahman & Das, 2021; Wu et al., 2023). Nevertheless, implementation feasibility is often

under-specified, particularly regarding connectivity requirements, data acquisition frequency, and the capability of end users to interpret and act on model outputs factors that strongly influence adoption in resource-limited settings (Hasibuan & Ramdani, 2023; Mahadi & Abdullah, 2021). These feasibility issues are addressed more directly in a smaller but important body of work on adoption barriers and ecosystem readiness in developing contexts. Studies discussing Indonesia and broader ASEAN conditions highlight constraints such as limited localized datasets, uneven digital literacy, and the need for partnership models that link academia, government, and agritech actors to deliver training, support, and affordable solutions (Gultom & Wahyuni, 2023; Lestari et al., 2024; Saputra et al., 2023; Sari & Putri, 2023). However, this evidence is often separated from the technical literature, leaving a synthesis gap: current research rarely connects AI techniques to functional roles and then to deployment readiness and smallholder feasibility in a single, systematic map.

To close that gap, this study conducts a Systematic Literature Review (SLR) to identify AI applications in poultry farming, classify them by functional domain, and synthesize reported benefits and limitations with explicit attention to implementation feasibility in UMKM contexts. The review organizes findings into core functions disease detection, environmental monitoring, behavior analysis, productivity optimization, and automation so that stakeholders can compare what is technically possible with what is realistically deployable under different farm conditions (Bhusal & Khanal, 2021; Huang & Yang, 2022; Wu et al., 2023). Based on the combined technical and adoption literature, this review argues that successful digital transformation in poultry farming depends less on model performance in isolation and more on the fit between AI functions and operational constraints especially affordability, data availability, integration complexity, and user capability. Accordingly, the working hypothesis is that low-cost monitoring and decision-support tools will show higher near-term feasibility and adoption potential for UMKM producers, whereas robotics-heavy automation will remain concentrated in industrial systems until costs decline and local support ecosystems and datasets mature (Al-Qurashi & Tashkandi, 2021; Mahadi & Abdullah, 2021; Wibowo & Utami, 2022).

RESEARCH METHOD

The unit of analysis in this study is peer-reviewed journal articles that report or evaluate the use of Artificial Intelligence (AI) in poultry farming. Each article is treated as

an analytical artifact from which evidence is extracted regarding the AI technique applied, the functional role in poultry production, the implementation context (laboratory vs. field; industrial vs. smallholder), and reported outcomes, benefits, and limitations. Thus, the study does not analyze individual farmers or farms as respondents; rather, it systematically analyzes the published evidence base during the selected period.

This research employs a Systematic Literature Review (SLR) design to consolidate a rapidly growing yet fragmented body of work on AI applications in poultry systems. An SLR is appropriate because it enables transparent identification, screening, and synthesis of studies across diverse engineering and animal-production contexts while reducing selection bias through predefined criteria and procedures. The review follows the PRISMA 2020 workflow to strengthen methodological traceability across identification, screening, eligibility, and inclusion stages and to ensure that the review can be replicated by other researchers.

The main information source is Scopus-indexed, open-access journal articles published from January 2020 to July 2025. Scopus indexing is used to maintain consistent publication standards, while the open-access restriction ensures that all included studies can be accessed and verified without subscription barriers. The scope is limited to poultry-specific AI applications in production and management contexts, and all records are restricted to English language articles. The inclusion and exclusion criteria are summarized in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Document type	Peer-reviewed journal articles	Conference papers, editorials, book chapters, theses
Indexing	Scopus-indexed journals	Non-indexed sources (unless explicitly allowed; not used here)
Access	Fully open access	Subscription-only or hybrid without full OA access
Language	English	Non-English publications
Time range	2020–July 2025	Published before 2020
Scope relevance	AI applied to poultry production/management	General livestock AI without poultry focus
Study content	Clear method and AI application details	Insufficient methodological description

Data collection was conducted through a structured database search followed by staged screening. A Boolean query was used: (“artificial intelligence” OR “machine learning” OR “deep learning” OR “computer vision”) AND (“poultry” OR “chicken” OR “broiler” OR “layer”) AND (“farming” OR “livestock” OR “agriculture”) AND (“monitoring” OR “disease detection” OR “automation” OR “behavior analysis”). Filters were applied for years (2020–2025), English language, journal articles, and open access. The initial search returned 219 records; after duplicate removal, 187 records were screened by title and abstract, producing 72 articles for full-text assessment. After eligibility assessment against Table 1, 28 studies were retained for final synthesis. The full selection pathway is summarized in the PRISMA flow diagram Figure 1.

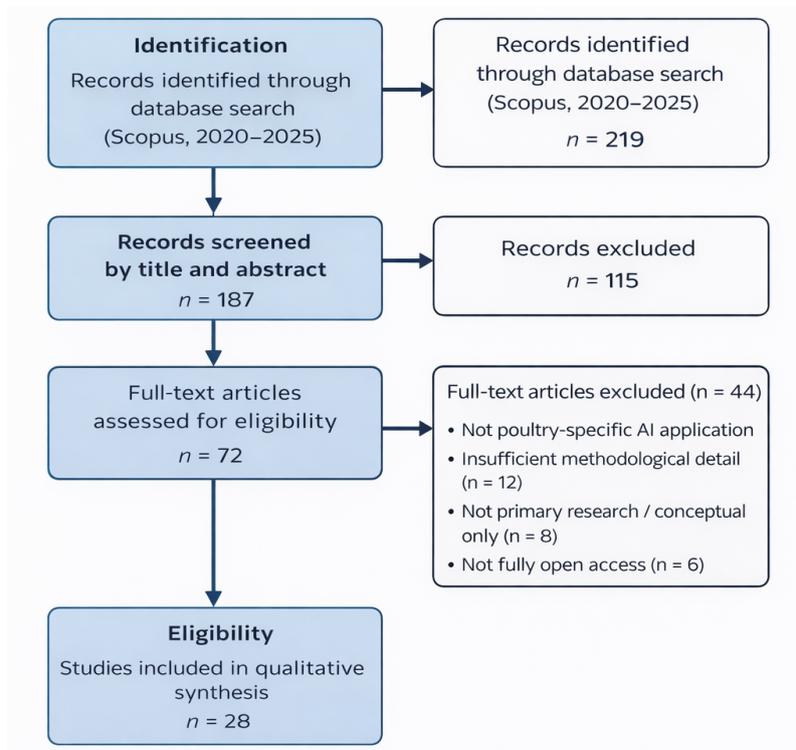


Figure 1. PRISMA flow diagram

The included studies were analyzed using thematic analysis supported by a standardized extraction form. Evidence from each article was extracted into predefined fields (Table 2) and coded into functional domains and implementation contexts. The synthesis grouped applications into five domains: (1) disease detection and health monitoring, (2) environmental monitoring and climate control, (3) behavior and welfare analysis, (4) productivity and feeding optimization, and (5) automation and robotics. Cross-study comparisons were then conducted to identify dominant AI techniques, commonly

used data modalities, reported performance measures, and recurring constraints (e.g., cost, dataset requirements, scalability) that influence feasibility in resource-limited and UMKM settings.

Table 2. Data Extraction Form and Coding Scheme

Extracted item	Description (what is recorded)	Example coding output
Bibliographic data	Author(s), year, journal	“Zhao et al., 2022; Animals”
Country/region	Study location or target context	Indonesia / ASEAN / global
Poultry system	Broiler/layer; housing type if stated	Broiler–closed house
AI technique	ML/DL/RL; specific model if stated	CNN / SVM / LSTM / RL
Data modality	Image, audio, sensor, multimodal	Audio + sensor fusion
Functional domain	Main function of AI application	Disease detection
Implementation context	Lab-scale vs field-scale; farm scale	Field pilot; smallholder
Outcomes/metrics	Accuracy, F1, MAE, energy saving, etc.	F1-score; MAE; % saving
Benefits	Reported practical advantages	Reduced labor, early warning
Limitations	Data, cost, transferability, infra	Labeling cost; low scalability
Adoption feasibility notes	Evidence relevant to UMKM readiness	Requires low-cost sensors

RESULT

Distribution of AI Applications in Poultry Farming

The evidence from the 28 included studies shows that AI applications in poultry farming cluster into five functional domains: disease detection and health monitoring, environmental monitoring and climate control, behavior and welfare analysis, productivity and feeding optimization, and automation and robotics. The distribution is summarized in Table 3. In essence, the literature concentrates most heavily on health-related monitoring, while automation and robotics receive the least attention. This pattern suggests four clear tendencies: (1) disease and health monitoring dominates because biosecurity risks are high-impact and monitoring is operationally actionable; (2) environmental control and productivity optimization appear at comparable levels, indicating parallel interest in improving housing stability and resource efficiency; (3) behavior and welfare analysis is moderately represented, reflecting increasing use of computer vision for welfare indicators; and (4) robotics remains limited, implying higher cost and integration barriers. Overall, the distribution implies that current AI adoption pathways are shaped by immediate feasibility and value monitoring and decision-support functions are prioritized over capital-intensive automation.

Table 3. Distribution of AI Applications Across Functional Domains

Functional Domain	Number of Studies	Percentage
Disease detection & health monitoring	8	28.6%
Environmental monitoring & climate control	6	21.4%
Behavior & welfare analysis	5	17.9%
Productivity & feeding optimization	6	21.4%
Automation & robotics	3	10.7%
Total	28	100%

After observing the distribution in Table 3, it becomes clear that AI research is currently driven by problems where early detection and continuous monitoring can produce immediate operational benefits. The comparatively low proportion of automation studies indicates that the field is still largely in a “decision-support” phase rather than a “full mechanization” phase, especially when cost and integration complexity are considered. This distribution also provides a practical baseline for identifying which functional areas are most mature and which areas represent opportunities for future engineering development and validation in real farm settings.

Technological Approaches and Data Modalities

Across the included studies, the second body of evidence concerns the dominant technological approaches and the data modalities that enable them. Table 4 summarizes how frequently major AI techniques appear and the types of data they commonly use. Put simply, deep learning is most prevalent, especially where image/video or time-series data is central, while classical machine learning remains important for multivariate prediction and classification. From this mapping, four trends emerge: (1) CNN/LSTM dominance reflects the strong role of vision-based monitoring and forecasting tasks in poultry systems; (2) RF/SVM remain widely used because many farm decisions still rely on structured variables such as environment, feed, and growth indicators; (3) reinforcement learning appears mainly in control problems such as ventilation and cooling where continuous optimization is needed; and (4) hybrid systems indicate movement toward integrated platforms combining sensors and analytics to produce actionable recommendations. The implication is that technology choice is closely tied to data accessibility and operational constraints: vision-heavy systems can be powerful but depend on data quality and generalizability, while sensor-based and hybrid systems may be more practical for continuous farm operation under resource limitations.

Table 4. AI Techniques and Data Modalities

AI Technique	Frequency	Typical Application	Data Type
Deep learning (CNN, LSTM)	11	Disease detection, vision-based monitoring, forecasting	Image, video, time series
Machine learning (RF, SVM)	7	Behavior classification, multivariate prediction	Multivariate/tabular
Reinforcement learning	4	Climate control optimization	Sensor streams
Hybrid AI systems	6	Integrated monitoring & decision support	Multimodal
Total	28		

Interpreting Table 4 suggests that the “dominant AI pathway” in poultry farming depends strongly on the type of signal being captured. Where farms can reliably collect visual or acoustic cues, deep learning tends to dominate; where farms depend on structured operational variables, conventional machine learning remains competitive and often more deployable. The emergence of hybrid systems is particularly important for implementation, because it indicates a shift from single-task algorithms toward end-to-end solutions that combine sensing, analytics, and decision support an essential direction if AI is to become a routine component of farm management rather than a stand-alone demonstration.

Implementation Context and Feasibility

The third evidence set addresses implementation maturity whether AI solutions are evaluated in laboratory settings, pilot/prototype farms, or full field deployments and what this implies for feasibility. Table 5 shows that most studies remain in laboratory or pilot phases, with fewer demonstrating deployment in real production conditions. Restated, the literature is rich in technical validation but thinner in sustained real-farm evidence. Four implementation tendencies stand out: (1) laboratory-based dominance indicates that algorithm development and controlled evaluation remain the main research mode; (2) pilot trials are growing, suggesting increasing effort toward realistic validation and early integration with farm routines; (3) full deployments remain limited, reflecting real-world barriers such as infrastructure readiness, maintenance burden, connectivity, and user training; and (4) studies with developing-country relevance more often emphasize low-cost sensors and simplified systems, signaling that feasibility strongly shapes design choices. The implication is that the main bottleneck is frequently deployment readiness rather than algorithmic capability; moving from proof-of-concept to scalable adoption requires

affordable hardware, stable data pipelines, and user-centered integration especially for UMKM contexts.

Table 5. Implementation Context of AI Systems

Implementation Level	Number of Studies	Key Characteristics
Laboratory / experimental setting	12	Controlled environment; strong technical validation; limited operational variability
Pilot or prototype farm	9	Partial real-world testing; early integration with farm routines
Full field deployment	7	Tested in production conditions; greater emphasis on usability, reliability, and cost
Total	28	

Table 5 highlights a consistent maturity gap: most published work still prioritizes technical proof under controlled conditions, while fewer studies provide evidence of sustained operation in commercial or smallholder environments. This imbalance matters because feasibility constraints hardware reliability, maintenance, connectivity, and training tend to surface only when systems run continuously in real farms. Consequently, the implementation distribution supports the argument that future research should prioritize longitudinal field validation and context adaptation, particularly for UMKM settings where the success of AI depends on low operational burden and clear cost–benefit justification.

DISCUSSION

Across the 28 studies synthesized in this systematic review, three findings consistently characterize the current landscape of AI-enabled poultry farming: research attention is concentrated on monitoring-oriented functions (especially disease/health and environmental control), deep learning particularly vision-based methods dominates many technical implementations, and most systems are still validated in laboratory or pilot settings rather than sustained real-farm operation. These patterns suggest that AI-driven digital transformation in poultry farming is progressing, but in an uneven and staged manner where adoption advances fastest in functions that deliver immediate operational value with comparatively low integration burden (Bhusal & Khanal, 2021; Huang & Yang, 2022; Wu et al., 2023).

A useful starting point for explaining why monitoring dominates is to consider the risk structure of poultry production. Disease events and suboptimal housing conditions can generate immediate economic losses through mortality, reduced growth, and deteriorating

feed conversion, making early detection and continuous monitoring high-priority targets for innovation. As a result, AI tools that provide early warning via images, sound, or sensor streams are particularly attractive because they can be introduced incrementally, often by overlaying analytics on existing routines without requiring major physical redesign of the production system (Mohammadrezaei et al., 2020; Neethirajan, 2020; Rahman & Das, 2021). By contrast, automation and robotics typically require higher capital expenditure, physical infrastructure changes, and ongoing maintenance capability, which helps explain why these applications appear less frequently in the evidence base and remain concentrated in more resource-rich contexts (Huang & Yang, 2022).

The technological distribution observed in the review further supports this explanation. Deep learning especially convolutional approaches used for images and videos frequently appears because many poultry-relevant indicators are inherently visual or behavioral (e.g., posture, activity patterns, crowding, and visible symptoms), making computer vision a natural pathway for detection and monitoring tasks (Kim & Lee, 2023; Zhao et al., 2022). At the same time, classical machine learning remains prominent in applications that rely on structured variables such as temperature, humidity, feeding records, and growth trajectories, which are common in predictive modeling and decision-support scenarios (Imran & Khan, 2022; Kassab & ElBanna, 2022).

Importantly, the presence of hybrid systems combining multiple data modalities suggests a gradual shift away from stand-alone model demonstrations toward integrated decision-support pipelines, aligning with broader trajectories described in reviews of smart livestock and poultry systems (Huang & Yang, 2022; Wu et al., 2023). The implementation maturity profile provides a complementary explanation for why strong technical progress does not automatically translate into widespread operational adoption. The review shows that many studies remain in laboratory or pilot phases, with fewer reporting full field deployments. This maturity gap is expected because real farms introduce variability and constraints that are difficult to reproduce in controlled settings: lighting changes, dust, humidity, housing differences, breed variability, sensor drift, and intermittent connectivity can degrade performance and reliability. These practical constraints help explain why high accuracy in experimental conditions often does not guarantee robust, continuous performance in production environments (Huang & Yang, 2022; Mahadi & Abdullah, 2021).

In addition, operational adoption requires more than model performance; it demands stable data pipelines, maintainable hardware, and user workflows that farmers can realistically operate over time, which are frequently underreported in technically oriented studies (Al-Qurashi & Tashkandi, 2021; Hasibuan & Ramdani, 2023). When compared with prior scholarship, the present synthesis aligns with broader conclusions that AI in animal agriculture is expanding rapidly but remains fragmented across domains and uneven in deployment readiness (Bhusal & Khanal, 2021; Wu et al., 2023). Where this review adds value is in connecting functional focus (what AI is used for), technological choice (how it is implemented), and maturity level (where it has been validated) into a single interpretive picture that clarifies why monitoring dominates and why robotics remains limited. This framing shifts the evaluation of “progress” away from algorithmic novelty alone and toward deployment feasibility, revealing that the key bottleneck often lies in implementation economics, infrastructure readiness, and local data adequacy rather than purely computational capability (Al-Qurashi & Tashkandi, 2021; Mahadi & Abdullah, 2021).

The implications are particularly salient for developing-country contexts, including Indonesia, where poultry production includes many small and medium enterprises (UMKM). Evidence on Indonesia and similar settings highlights barriers such as high upfront sensor/IoT costs, limited digital literacy, uneven internet connectivity, and scarcity of localized datasets for local breeds and tropical conditions (Indonesia, 2022; Saputra et al., 2023; Wibowo & Utami, 2022). These barriers help explain why low-cost and modular monitoring systems are frequently positioned as the most realistic near-term pathway: they can deliver tangible value (early warning and basic decision support) without requiring large-scale infrastructural transformation. Partnership-oriented approaches linking academia, government, and startups also emerge as a practical mechanism for accelerating adoption through co-development, training, and support ecosystems (Lestari et al., 2024; Sari & Putri, 2023).

A balanced reflection must also consider potential dysfunctions alongside benefits. On the positive side, AI-based monitoring and decision support can improve efficiency, reduce mortality risk, stabilize environmental conditions, and support welfare-oriented management by enabling earlier intervention and more data-driven decisions (Huang & Yang, 2022; Wu et al., 2023) On the negative side, unequal access to technology may widen productivity gaps between large integrators and smallholders, especially if advanced tools

remain expensive or require specialized maintenance. There is also the risk that models trained on non-local data perform poorly in local contexts, producing recommendations that are less reliable for local breeds or climate conditions, which reinforces the need for localized datasets and context-aware evaluation (Al-Qurashi & Tashkandi, 2021; Mahadi & Abdullah, 2021). Finally, dependence on proprietary platforms may reduce farmer autonomy if systems are not transparent or if users cannot validate and adapt recommendations.

From an action and policy perspective, the evidence supports several priorities. First, technology development and deployment should prioritize affordable, modular solutions particularly monitoring and basic decision-support tools that can operate with low-cost sensors and limited connectivity. Second, building and sharing localized datasets and benchmarks is essential to improve robustness across housing systems, breeds, and tropical environments, thereby reducing the generalizability gap that limits real-world performance. Third, capacity-building programs for farmers and technicians should be treated as a core component of digital transformation, not an afterthought, because operational success depends on sustained use and maintenance (Hasibuan & Ramdani, 2023; Wibowo & Utami, 2022). Finally, coordinated partnerships among universities, government agencies, and agritech firms can help translate promising pilots into scalable deployments through financing models, training, and infrastructure support particularly for UMKM producers (Lestari et al., 2024; Sari & Putri, 2023). Together, these steps position AI not only as a technical innovation, but as a socio-technical pathway toward more resilient and inclusive poultry production systems.

CONCLUSION

This study offers a clear lesson from the evidence: Artificial Intelligence (AI) is already reshaping poultry farming primarily through monitoring and decision-support functions including automated disease detection, behavior and welfare monitoring, environmental control, feed optimization, and productivity forecasting yet the pace and depth of transformation depend strongly on implementation feasibility. Across the 28 reviewed studies, AI demonstrates consistent potential to improve efficiency, animal welfare, and sustainability, but adoption remains uneven, especially in developing contexts where smallholder and UMKM producers face cost, infrastructure, and capability constraints.

Scientifically, this review contributes by providing a function-oriented synthesis of AI applications in poultry farming and linking three dimensions that are often discussed separately: functional domains of application, dominant technological approaches, and implementation maturity and feasibility signals. By organizing the literature around operational functions rather than isolated algorithms, the study clarifies which AI applications are most developed, where evidence is still limited (particularly full field deployment), and how these patterns relate to real-world constraints relevant to Indonesia and similar settings. This integrated mapping can support future engineering design choices, evaluation priorities, and policy interventions aimed at inclusive digital transformation.

This study also has limitations. The review was restricted to open-access, Scopus-indexed journal articles published between 2020 and July 2025, which may exclude relevant evidence from subscription-based journals, conference proceedings, and grey literature sources that may contain important implementation reports and industry pilots. In addition, heterogeneous reporting across studies limits direct quantitative comparison of performance metrics and cost–benefit outcomes. Future research should therefore expand coverage beyond these boundaries, develop and share localized datasets (including for local breeds and tropical conditions), and prioritize longitudinal field evaluations that report usability, maintenance, and economic feasibility. Such efforts will strengthen the evidence needed to scale AI solutions responsibly and effectively, enhancing food security, rural livelihoods, and animal health in Indonesia and globally.

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