JWPR
Journal of World's Poultry Research

2025, Scienceline Publication
J. World Poult. Res. 15(4): 490-502-, 2025

Systematic Review
DOI: https://dx.doi.org/10.36380/jwpr.2025.47
PII: S2322455X2400047-15

ISSN: 2322-455X

The Integration of Artificial Intelligence and Internet of Things in Ventilation Systems of Closed Houses in Broiler Chicken Farms of Indonesia: A Literature Review

Muhammad Irfan Maulana* and Indrawati Yudha Asmara

Faculty of Animal Husbandry, Padjadjaran University, Sumedang, 54363, Indonesia

*Corresponding author's E-mail: muhammad20125@mail.unpad.ac.id

Received: September 28, 2025, Revised: October 26, 2025, Accepted: November 22, 2025, Published: December 31, 2025

ABSTRACT

The closed house system has been widely adopted in Indonesia due to its ability to control the microclimate; however, its implementation still faces several challenges, including high investment costs, limited monitoring, and maintenance management that is not yet adaptive. This literature review aimed to analyse the design of Artificial Intelligence (AI) and Internet of Things (IoT) integration in the automatic ventilation control system of broiler chicken closed houses in Indonesia. The method employed is a systematic review of relevant international and national articles. The literature review followed PRISMA guidelines, identifying 28,827 publications on AI and IoT, filtered to 636 studies on poultry and 335 studies on AI–IoT-based monitoring systems. Ultimately, 98 articles met the inclusion criteria, including 20 studies specifically focused on studies in Indonesia. The findings indicated that AI–IoT integration has the potential to improve energy efficiency, optimize the microclimate, such as temperature, humidity, velocity, and support broiler chicken welfare through data-driven monitoring and automated decision-making systems. Nevertheless, the adoption of this technology continues to face challenges such as high initial costs, limited energy and internet infrastructure, and the digital skills gap among farmers.

Keywords: Adaptive ventilation, Energy-efficient, Microclimate, Poultry production, Smart farming, Tropical climate

INTRODUCTION

Broiler chicken production plays a vital role in ensuring global food security, contributing more than one-third of total meat consumption worldwide due to its efficiency and affordability. In Indonesia, poultry meat, particularly broilers, is the main source of animal protein, with production exceeding 717 thousand tons per year (Center for Agricultural Data and Information System, 2024). The industry's rapid growth reflects both global and domestic demand trends, yet maintaining productivity and welfare under Indonesia's tropical conditions remains a significant challenge. Consequently, technological innovation in climate control and housing systems has become essential to sustain growth and competitiveness.

The modern broiler farming industry increasingly adopts closed house systems, which minimize adverse environmental effects and climate fluctuations, creating a thermoneutral zone optimal for growth and health (Pakage et al., 2020). This system automatically regulates temperature, humidity, air velocity, and air quality (O_2, CO_2, NH_3) according to the broiler chicken requirements (Syahrorini et al., 2020). Compared with open houses, closed houses reduce disease risks, improve growth efficiency, and enhance feed conversion (Abd-El Hamed et al., 2025).

Broiler chickens require proper environmental conditions throughout growth phases, making ventilation management crucial (Saner and Shekhawat, 2022). Poor ventilation causes stress, reduced feed intake, growth issues, and even mortality (Tainika et al., 2023). Most ventilation systems regulated by climate control in closed houses primarily focus on desired temperature and humidity levels (Setiadi et al. 2018). However, to create more appropriate conditions, other factors should also be considered, such as air velocity, external temperature, humidity, and ventilation needs based on the actual condition of the chickens, including age, stocking density, body weight, harmful gas concentrations, and microclimate distribution within the house (Curi et al., 2017; Syahrorini et al.,, 2020). Thus, recalibration of systems is needed to align microclimates with animal comfort (Detsch et al., 2018). In this context, automation becomes essential for precise regulation and quick adaptation to environmental changes (Detsch et al., 2018).

Technological advances have introduced the Internet of Things (IoT) in livestock housing for real-time condition monitoring (Umapathi et.al, 2025). The IoT enables data collection from sensors tracking temperature, humidity, and air quality, accessible to farmers for enhanced decisions (Debauche, 2020; Jebari et al., 2023). Integration with Artificial Intelligence (AI) allows analysis of complex datasets, pattern recognition, and automated decision-making for ventilation (Yang et al., 2019; Debauche, 2020). Combined AI and IoT can optimize closed house management in real time, improving both productivity and animal welfare; however, adoption in Indonesia faces challenges. The tropical climate with high temperatures, unpredictable weather, and regional variation limits ventilation system effectiveness (Oke et al., 2024). Economic and infrastructural factors also play major roles in modern farming. Modern closed houses require large investments, rural areas often lack stable electricity and internet, and many farmers lack skills in operating automated systems.

Although studies on closed houses, IoT, and AI exist, most emphasize condition monitoring, fuzzy logic-based temperature–humidity control, or mathematical ventilation modelling (Husein and Kharisma, 2020; Saner and Shekhawat, 2022). Few studies have examined the comprehensive integration of AI and IoT for adaptive climate control systems specifically designed for Indonesia's tropical conditions, particularly regarding environmental fluctuations, microclimate distribution, infrastructure limitations, and farmer capacity gaps. Therefore, this article aimed to present an automated ventilation control design integrating climate control with AI and IoT in broiler chicken farms of Indonesia.

MATERIALS AND METHODS

This study employed a systematic literature review method to examine the integration of AI and IoT in ventilation systems of closed-house broiler farms in Indonesia. Literature was collected from international and national databases, including Scopus, ScienceDirect, Google Scholar, and SINTA, using keywords such as "Closed House Poultry Ventilation", "Artificial Intelligence in Broiler Farming", "Internet of Things (IoT) in Poultry", "Smart Poultry Farming", and "Climate Control" in Tropical Poultry Houses.

The review process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and reproducibility. An initial search identified 28,827 publications related to AI and IoT applications. After applying domain filters, 636 studies focused on poultry, and 335 studies discussed monitoring systems using AI–IoT integration. Following screening based on relevance, duplication, and data completeness, 98 studies were deemed eligible for inclusion in this review, and 20 very specific studies were relevant to the application of AI and IoT in Indonesia.

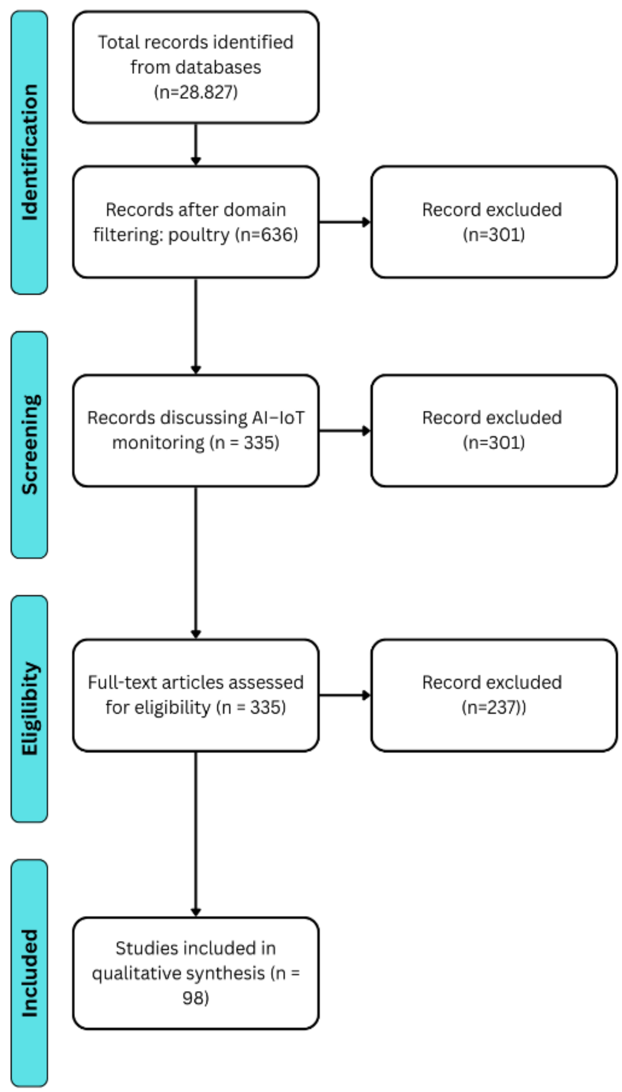

Figure 1. The PRISMA flow diagram for choosing the articles in this study

Inclusion criteria comprised peer-reviewed articles, conference proceedings, and reports published between 2014 and 2024 that addressed AI–IoT integration, ventilation, or microclimate control in broiler production. Exclusion criteria removed non-scientific publications, popular articles, and studies outside the poultry domain. Screening was performed in three stages: title review, abstract review, and full-text assessment.

The selected articles were analysed qualitatively by extracting information on objectives, methods, findings, and limitations. Following the screening process, the selected studies were systematically analysed and grouped into several thematic domains related to closed-house ventilation systems, IoT integration, AI applications, tropical climate challenges, and implementation perspectives in Indonesia. During this stage, findings from each theme were qualitatively synthesized to identify prevailing study trends, existing knowledge gaps, and potential innovation opportunities for the development of AI–IoT-based adaptive ventilation systems in Indonesian broiler production.

OVERVIEW OF LITERATURE SELECTION

Among the 98 studies included, 20 were identified as highly relevant to the application of AI and IoT in Indonesia's closed-house broiler systems. Overall, these studies highlight that integrating both technologies enhances energy efficiency, stabilizes the microclimate, and improves broiler welfare through real-time, data-driven automation.

Early Indonesian studies applied IoT-based temperature and humidity sensors (DHT22) integrated with ESP32 or Raspberry Pi microcontrollers for microclimate monitoring (Fathurohman et al., 2023; Tambunan and Apryanto, 2024). These systems achieved over 90% accuracy at approximately 10-15% of the cost of commercial systems. Nalendra and Waspada (2021) added automatic fan speed control using Pulse Width Modulation (PWM), while Utomo et al. (2019) emphasized the need to integrate ventilation with automated feeding systems.

A study by Husein and Kharisma (2020) and Rosmasari et al. (2025) utilized AI-based fuzzy logic and naïve Bayes Gaussian algorithms for real-time classification of housing conditions. These models detected environmental anomalies and adjusted ventilation automatically. Fahrurrozi et al. (2024) and Safputra et al. (2023) integrated load-cell sensors and IoT-based feeder controls, improving feed efficiency and reducing mortality rates. From a networking perspective, Fathurohman et al. (2023) and Hambali et al. (2020) demonstrated the importance of wireless sensor networks for reliable data transmission. Wicaksono et al. (2017) pioneered the use of wireless sensor–based temperature control, while Liani et al. (2021) combined LoRaWAN and fuzzy logic to dynamically adjust ventilation according to broiler growth stages.

In terms of AI, Ribeiro et al. (2019), Kiruthika et al. (2024), and Reddy et al. (2024) reported that Artificial Neural Network (ANN) and Support Vector Machine (SVM) models were most effective for temperature–humidity prediction, achieving less than 5% error rates. Barsagadea et al. (2024) and Bharanishree et al. (2025) developed machine learning–based climate control systems that reduced heat stress by up to 25%. Collectively, these findings suggest that AI–IoT adoption in Indonesia has advanced to experimental and semi-commercial stages, emphasizing tropical adaptation, cost efficiency, and infrastructure constraints. The main challenges include unstable electricity and internet access in rural areas and limited digital literacy among farmers. Nonetheless, current study directions point toward machine-learning-driven adaptive ventilation systems capable of adjusting to environmental and behavioral variations in real time.

THEMATIC SYNTHESIS OF FINDINGS

Closed house systems and implementation challenges

In closed house systems, two main ventilation types are used, such as cross ventilation and tunnel ventilation (Figure 2). The types of ventilation differ in airflow direction and distribution, which influence microclimate control. Cross ventilation moves air horizontally through sidewalls, using large exhaust fans on one side and window-like inlets on the opposite (Ghasemi et al., 2025). This negative-pressure design distributes air across the house and works well in small to medium houses, but in longer houses it creates circulation inefficiencies or "dead zones" (Bustamante et al., 2013; Ghasemi et al., 2025). Cross ventilation also produces relatively low air velocity (0.60 ± 0.56 m/s to 0.64 ± 0.54 m/s), making it less effective against heat stress in summer (Wheeler et al., 2003; Bustamante et al., 2013). Tunnel ventilation moves air longitudinally from front to back under negative pressure created by high-capacity exhaust fans. It is characteristic design includes multiple exhaust fans arranged at one end of the house, while the opposite end is typically equipped with cooling pads serving as inlets (Du et al., 2019). This setup draws cool air through the pads, distributing it rapidly along the house. Tunnel ventilation significantly reduces heat stress by increasing air velocity, which enhances sensible heat loss from the birds (Dozier et.al., 2006).

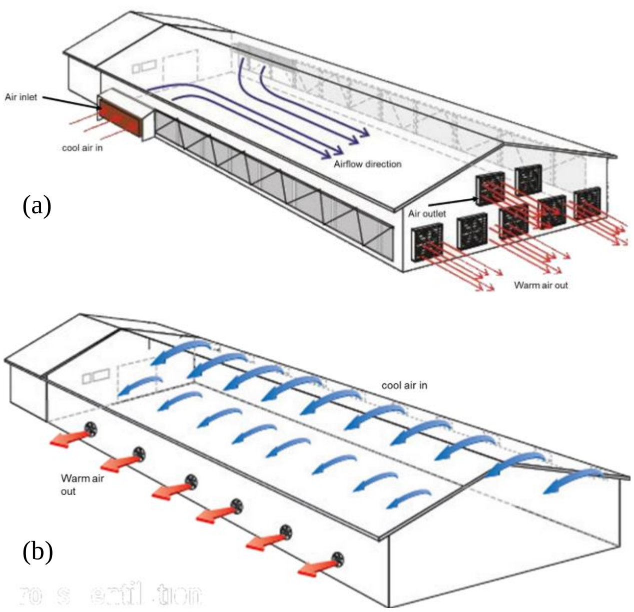

Figure 2. Schematic comparison of tunnel **(a)** and cross **(b)** ventilation in closed house systems. Source: Jongbo (2020).

In advanced broiler farming, closed house ventilation emphasizes energy efficiency, productivity, and animal welfare (Sans et al., 2021). Subtropical climates with sharp diurnal and seasonal variations require precise microclimate control (Al-Chalabi et al., 2017). Studies showed negative-pressure systems can regulate temperature and humidity in winter, though uneven heat distribution persists (Al-Chalabi et al., 2017). These systems are designed to expel harmful gases like ammonia and carbon dioxide, maintaining concentrations below harmful thresholds (Costantino et al., 2020).

Ventilation in subtropical countries faces seasonal challenges, such as winter, which must increase heating needs, and while summer demands efficient cooling to maintain the performance of the broiler. Developed countries have applied automation integrating exhaust fans, heaters, and cooling pads, digitally managed via IoT platforms for real-time monitoring and adjustments, improving stability and energy efficiency year-round (Oliveira et al., 2024). Additional innovations include thermal insulation, Computational Fluid Dynamics (CFD) supported airflow design, and improved tunnel/sidewall management (Saraz et al., 2017; Küçüktopçu et al., 2024).

Subtropical regions require dynamic strategies to handle moderate but fluctuating climates (Afeez et al., 2019).

In contrast to tropical systems, subtropical systems focus on mitigating variable heat stress with proactive control. IoT applications typically employ fewer but strategically placed sensors, while CFD modelling plays a central role in optimizing airflow, ventilation efficiency, and sensor placement (Chen et.al., 2021). Techniques such as Renormalization Group k-epsilon (RNG k-ε) and Large Eddy Simulation (LES) improve air exchange, reduce blind spots, and guide optimal fan and cooling pad layouts to address seasonal variability (Lee et al., 2007; Pourvosoghi et al., 2018).

Closed house systems in Indonesia

In Indonesia, closed house systems typically use tunnel ventilation combined with evaporative cooling pads (Lillahulhaq et al., 2024). These pads lower incoming air temperature through water evaporation, highly relevant to the hot tropical climate. Studies showed this combination maintains indoor temperatures 3–5°C below the outside environment while keeping humidity at safe levels (Xin et al., 2017; Saner and Shekhawat, 2022). The working mechanism of evaporative cooling pads is illustrated in Figure 3.

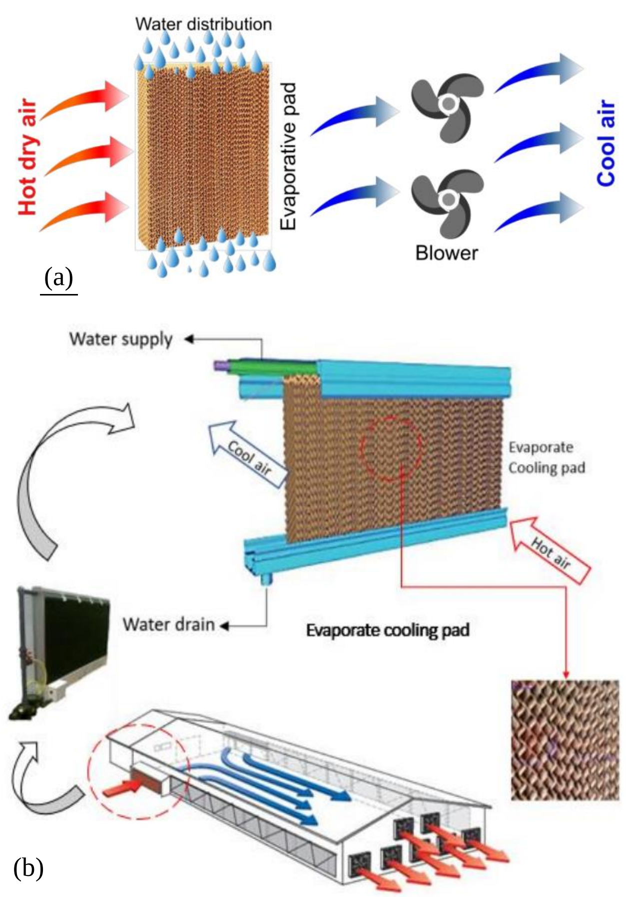

Figure 3. Working mechanism of evaporative cooling pads in closed house systems. Sources: **(a)** Shahzad et al., 2021; **(b)** Lillahulhaq et al., 2024.

This system uses porous pads continuously supplied with water, ensuring they remain moist (Shahzad et al., 2021). When hot external air is drawn by exhaust fans through the wet pad surface, water flows downward via gravity and capillary action (Laknizi et al., 2019). As the warm air passes through, part of its heat evaporates the water. Continuous evaporation (adiabatic process) produces a cooling effect until saturation, where air enthalpy remains constant while humidity increases (Mahmood et al., 2016). This system uses exhaust fans to create a negative pressure inside the broiler house, which pulls cooler air from outside into the house. This method is effective in distributing air evenly and maintaining a comfortable temperature for the broilers (Setiadi et al., 2018)

Despite its effectiveness, Indonesia's tropical climate presents challenges. During the rainy season, humidity often exceeds 80%, reducing ventilation efficiency and degrading litter quality. Wet litter encourages bacterial and fungal growth, increasing risks of respiratory diseases and skin problems such as dermatitis and hock burns (Kaukonen et al., 2016). High humidity also accelerates the increase in ammonia (NH_3) levels, damaging the respiratory tract, lowering feed intake, and impairing growth (Beker et al., 2004; Swelum, 2021). The negative effects of this situation can be minimized by integrating IoT into the cage ventilation system. Harrouz et al. (2021) note that in hot, humid climates, hybrid systems combining evaporative cooling with IoT-controlled dehumidifiers are more effective. Conversely, in the dry season in Indonesia, daytime temperatures often exceed 34-36°C, causing heat stress manifested as panting, reduced feed intake, and acid–base imbalance (Wasti et al., 2020). Prolonged stress worsens feed conversion, weakens immunity, and increases mortality (Abo-Al-Ela et al., 2021). Internet of Things (IoT) integrated ventilation systems can minimize hot ambient temperatures to enhance climate control, automating fans and heaters for optimal conditions (Afeez et al., 2019).

These challenges showed that closed houses require smarter, more adaptive technologies. Integrating AI with IoT offers a promising solution through real-time climate monitoring, AI-based pattern recognition, and automatic ventilation adjustments based on environmental conditions and actual broiler chicken needs (Debauche et al., 2020). International studies confirm AI–IoT integration improves energy efficiency, reduces heat stress, and enhances welfare via precise ventilation control (Jabade et al., 2024; Chen et al., 2021).

Internet of things and artificial intelligence

The Internet of Things integrates physical components and sensing devices into an internet-based network that supports real-time data gathering and analytical processing (Nuanmeesri and Poomhiran, 2020). It is defined as a system of interdependent devices, objects, and individuals with unique identifiers that transfer data across networks without requiring direct human interaction (Jebari, 2023). The IoT has significantly impacted livestock farming, especially broiler production, by improving resource management and environmental monitoring (Teng, 2015; Adli et al., 2025).

Internet of Things applications in poultry farming allow farmers to collect data from various sensors installed in the house, including temperature, humidity, microclimate components, as well as animal health and welfare status (Jabade et al., 2024). These sensors can measure parameters such as air quality, temperature, humidity, and animal activity (Yang, 2019). The data collected are then transmitted to an internet-connected digital platform, where farmers can access and analyse information in real time (Husein and Kharisma, 2020). Several studies have been conducted on IoT integration in broiler farming, as summarized in Table 1.

Integrated IoT–AI microclimate monitoring systems on closed house broiler cages are designed to stabilize environmental parameters. Sensor networks typically include temperature–humidity devices (DHT11, DHT22, DS18B20, BME280), gas sensors (MQ-135, MQ-137), and photodiode-based light sensors (Pereira et al., 2020; Fathurohman et al., 2023). These are connected to microcontrollers such as ESP8266 or Raspberry Pi for cost-effective monitoring. IoT prototypes achieve correlations above 0.90 with commercial devices at ~13% of the cost (Pereira et al., 2020; Tambunan and Apryanto, 2024).

Sensor placement is guided by Computational Fluid Dynamics (CFD) simulations to map airflow, temperature, and humidity, identifying heat or moisture accumulation zones that could induce heat stress in broilers (Drewry et.al, 2017). Sensors are then positioned at floor, midsection, and ceiling levels (Saraz et al., 2017; Faridah et al., 2021; Küçüktopçu et al., 2024). Field validation is conducted to ensure consistency between CFD models and real conditions (Heymsfield et al., 2018). Advanced methods such as clustering, Standardized Euclidean Distance (SED), and Geographic Information System (GIS) optimize spatial distribution to detect microclimate heterogeneity (Trane et al., 2023; Zanchi et al., 2024).

Collected data undergo multi-sensor fusion using methods such as the Kalman Filter for dynamic integration and convex optimization to exclude faulty data (Zhang et al., 2014; Sarbishei et al., 2013). AI models such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) estimate gas concentrations, enhancing air quality assessments (De Vito et al., 2007). Edge computing devices (Raspberry Pi, Jetson Nano, ESP32) locally process data to reduce latency, lower cloud costs, and maintain reliability during internet disruptions (Li et al., 2021; Priyanka et al., 2023). Edge computing is supported by microservices architecture with containerization, enabling lightweight, flexible, and scalable AI model deployment (Al-Doghman et al., 2023; Araújo et al., 2024).

Table 1. Studies on Internet of Things and artificial intelligence integration in broiler chicken farming in Indonesia

Author(s)	Year	Technologies and tools	Parameters observed	Key findings
Wicaksono et al.	(2017)	IoT, WSN, Xbee	Temperature, Humidity	The system maintained a heat index of 25°C
Hambali et al.	(2020)	IoT, WSN	Temperature, Humidity, Air Quality, Feed Feeder	The prototype reduced the mortality rate, provided automatic notifications
Revanth et al.	(2021)	IoT, Temperature, Humidity, Air Quality, Light Intensity, Litter Moisture Sensors	Temperature, Humidity, NH_3, Air Quality, Light Intensity, Litter Moisture	IoT-based poultry house environmental monitoring system
Liani et al.	(2021)	IoT, LoRaWAN, DHT22, Fuzzy Logic	Temperature, Humidity	Monitoring system adjusted to broiler growth stages
Ibrahima and Cissé	(2022)	IoT, DHT22, MQ137, Arduino Nano IoT 33	Temperature, Humidity, NH_3	Data stored and displayed on a cloud-based dashboard
Safputra et al.	(2023)	ESP32, DHT22, RTC Module, Load Cell Sensor	Temperature, Humidity, Feed	Accurate monitoring and parameter control with set points
Fathurohman et al.	(2023)	IoT, DHT22, MQ-135, Anemometer, NRF24L01, ESP32, ATmega328P	Temperature, Humidity, NH_3, Wind Speed	Wireless transmission of microclimate data in real-time
Jebari et al.	(2023)	IoT, AI, Edge Computing, E-GRU	Temperature, Humidity, NH_3, CO, CO_2, CH_4, H_2S	Modular system enabling accurate data collection and environmental prediction
Sukri et al.	(2023)	IoT, K-Nearest Neighbour, Temperature and Humidity Sensors	Temperature, Humidity	The system effectively measured temperature, humidity, and distance for feed efficiency
Lashari et al.	(2023)	IoT, Temperature, Humidity, O_2, CO_2, CO, NH_3 Sensors	Temperature, Humidity, O_2, CO_2, CO, NH_3	Successfully maintained optimal climate and monitored harmful gases
Ghandi	(2023)	IoT, ARM Cortex M3 – LPC1769, LoRa, Jetson Nano	Temperature, Humidity	Achieved 99.72% accuracy in environmental condition classification
Jabade et al.	(2024)	IoT, DHT11	Temperature, Humidity	Alerts are sent to the smartphone when parameters exceed thresholds
Kiruthika	(2024)	IoT, SVM	Temperature, Humidity, Feeding, Disease	The SVM model predicted broiler growth with 90% accuracy
Reddy et al.	(2024)	IoT, CNN, Temperature, Humidity, Air Quality Sensors	Temperature, Humidity, Air Quality	Real-time optimization of poultry house environment using deep learning
Gowri et al.	(2024)	IoT, WSN, DenseNet	Temperature, Humidity, Air Quality, Feed	The prototype reduced mortality through automated corrective actions
Fahrurrozi et al.	(2024)	IoT, Random Forest ML	Temperature, Humidity, NH_3	The prediction model achieved 96.67% accuracy for poultry house conditions
Barsagadea et al.	(2024)	IoT, Temperature, Humidity, NH_3, Light Intensity Sensors	Temperature, Humidity, NH_3, Light Intensity	Real-time monitoring system for poultry house conditions
Da Silva et al.	(2025)	IoT, Fuzzy Logic	Temperature, Humidity	The climate control system achieved 98% validation accuracy
Rosmasari et al.	(2025)	IoT, BME-680, MICS-5524	Temperature, Humidity, NH_3	The monitoring system reached 82.03% accuracy in recording microclimate conditions
Bharanishree et al.	(2025)	IoT, DHT11, OpenCV, CNN, ThingSpeak	Temperature, Humidity, Broiler Health	The system predicted health issues and provided corrective recommendations

Note: IoT: Internet of things, WSN: Wireless sensor network, LoRaWAN: Long range wide area network, DHT: Digital humidity and temperature sensor, MQ: Metal oxide gas sensor, ESP: Espressif microcontroller, RTC: Real time clock, ANN: Artificial neural network, SVM: Support vector machine, CNN: Convolutional neural network, GRU: Gated recurrent unit, NH_3: Ammonia, CO_2: Carbon dioxide, CO: Carbon monoxide, CH_4: Methane, H_2S: Hydrogen sulfide.

During data processing, AI algorithms are applied to predict and control microclimate conditions in real time (Morozova, 2024). The Gated Recurrent Unit (GRU) model is preferred due to its computational efficiency and fewer parameters, making it suitable for edge devices with limited resources (Yang et al., 2020; Zarzycki and Ławryńczuk, 2021). Models based on Long Short-Term Memory (LSTM) and its bidirectional variant (BiLSTM) achieve superior predictive performance on long-sequence datasets but demand higher computational power (Yan et al., 2024; Saifullah, 2025). Convolutional Neural Networks (CNN) combined with attention mechanisms are also employed to extract spatio-temporal features from sensor data, enhancing the prediction accuracy of microclimate dynamics inside the house (Jia et al., 2024; Suresh et al., 2025).

Artificial Intelligence (AI)-driven ventilation systems often employ Artificial Neural Networks (ANN) to regulate water, feed, ventilation, temperature, and humidity (Morozova, 2024). Artificial Neural Network (ANN) models learn continuously by updating parameters and using classification errors to improve accuracy (Azadeh et al., 2014). Other studies also highlight the use of perceptron models, a simple form of ANN and a deep learning method, commonly applied to regression and classification tasks (Perrota, 2020). Figure 4 illustrates the learning model structure of neural networks. Hybrid control systems combine interpretable rule-based control (RBC) with adaptive machine learning, ensuring safety during critical events while enabling flexible responses to dynamic environments (Drgoňa et al., 2018; Aksjonov and Kyrki, 2023).

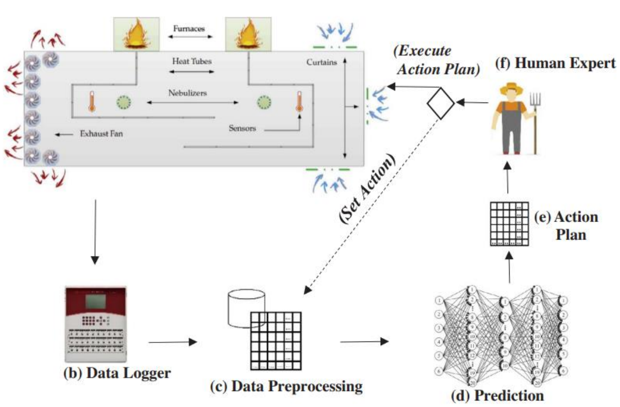

Figure 4. The learning model structure of neural networks. Source: Ribeiro (2019).

Beyond environmental parameters, AI integrates microclimate data with computer vision to monitor broiler chickens' behaviour and welfare. Gated Recurrent Unit (GRU), Support Vector Machine (SVM), Random Forest, and Computer Neural Network (CNN) models detect diseases, stress, or abnormal behaviours (Ahmed et al., 2024; Taleb et al., 2025). Computer vision technologies such as YOLOv5 can recognize chicken behaviours in real time, supporting the detection of early disease symptoms or reduced productivity (Guo et al., 2025). These systems include mobile notifications to alert farmers for timely interventions (Elango et al., 2024).

In Indonesian applications, AI algorithms are commonly integrated with Arduino-based IoT systems. Sensors such as DHT22 monitor temperature and humidity (Fathurrohman et al., 2023), and blower fan speed control using Pulse Width Modulation (PWM) methods (Nalendra, 2021). Air quality monitoring employs oxygen, CO_2, and NH_3 sensors like NDIR CO_2, MQ135, MQ7, and MCIS-6814 (Fathurrohman et al., 2023; Mulling et al., 2023). Data processed via embedded AI algorithms generates control signals to automatically regulate poultry house equipment.

Challenges in implementing closed-house systems

One of the primary challenges in adopting IoT–AI technologies in closed-house poultry systems is the high initial investment cost. Farmers must install integrated infrastructure, including temperature, humidity, and ammonia sensors; actuators such as fans, cooling pads, and heaters; and hardware components like data loggers, edge devices, and cloud servers. These devices are costly, particularly for small- and medium-scale farmers (Alkhafaji et al., 2024; Wah, 2025). High upfront costs increase production expenses, potentially reducing broiler competitiveness unless efficiency gains offset the investment.

Beyond costs, reliable devices are essential. Sensors must withstand extreme barn conditions, high temperature, humidity, dust, and ammonia, yet low-cost sensors are often inaccurate or unreliable, while high-quality ones remain expensive (Chojer et al., 2022). The AI applications also demand advanced computing infrastructure, whether through edge devices or stable cloud services (Prangon and Wu, 2024). Consequently, IoT–AI systems are mostly deployed in pilot projects or by large integrators, while adoption among independent farmers remains limited (Abiri, 2023). Additional concerns include technical complexity, data privacy, and cybersecurity risks. Solutions such as federated learning reduce data transmission requirements, while blockchain ensures transparency and security (Rahaman et al., 2024;

Cai et al., 2025; Potdukhe et al., 2025). Cost-efficient modular approaches based on LoRaWAN and open-source platforms are also being developed to support smallholder farms (Finistrosa et al., 2025).

Internet connectivity poses another critical barrier. Internet of Things and AI on closed-house systems rely on continuous real-time data transmission to function effectively (Haseeb et al., 2017). However, many Indonesian broiler farms are located in rural areas with poor internet infrastructure (Ullah, 2024). Disruptions in connectivity compromise monitoring systems and increase farmers' workload, undermining the potential benefits of automation.

Farmer management practices also affect implementation. Many Indonesian farmers continue to follow generalized Standard Operating Procedures (SOPs) provided by companies rather than adjusting ventilation to actual broiler chicken responses. Ventilation equipment fans, pads, and exhausts are often operated on fixed schedules rather than real-time behavioural cues, even though chickens are sensitive bioindicators of microclimate changes (Sohsuebgarm et al., 2019; Belykh et al., 2021). Reliance on subjective observations, such as smell or visual inspection, often delays responses to issues like high humidity or ammonia buildup. The inability to adapt ventilation promptly results in mismatched environmental conditions, reducing efficiency (George and Hovan, 2023).

Another challenge is the digital skills gap. Most Indonesian broiler farmers rely on experience-based management and are unfamiliar with digital tools for microclimate monitoring or data analysis. Many lack the ability to interpret sensor outputs, understand AI models, or utilize cloud-based applications effectively (Alkhafaji et al., 2024). This gap is linked to limited education and insufficient technical training from government institutions (Slayi et al., 2023). Consequently, even when devices are installed, usage often remains suboptimal.

Resistance to new technology further slows adoption. Farmers frequently perceive IoT–AI systems as costly, complex, and uncertain in terms of profitability (Vuka and Wu, 2024). Early negative experiences, such as frequent breakdowns or difficulties operating automated systems, reinforce this skepticism (Postolache et al., 2025). Cultural reliance on intuition and generational practices also contributes to reluctance (Sädeharju, 2025). Many farmers prefer intuitive decision-making based on experience rather than formal decision-support tools informed by data.

Addressing these challenges requires integrated government and private sector involvement. Financial incentives such as subsidies can reduce high upfront costs, while training programs help bridge the digital skills gap (Chen et.al., 2023). Public–private partnerships involving government, industry, and educational institutions are essential to provide infrastructure, technical support, and knowledge transfer. Additionally, developing affordable, context-specific IoT–AI models tailored to Indonesian infrastructure limitations is crucial to foster widespread adoption in poultry production.

CONCLUSION

The combination of IoT sensors with AI algorithms enables early detection of environmental changes, real-time ventilation adjustments, and more precise climate control. However, implementation at the farm level remains limited due to high construction costs, inadequate electricity and internet infrastructure in rural areas, and farmers' limited technical skills. Therefore, feasible solutions should focus on developing cost-effective and tropical-resistant technologies, improving access to digital infrastructure, and implementing training programs to strengthen human resource capacity.

DECLARATIONS

Acknowledgements

The authors would like to express their sincere gratitude to the Rector of Universitas Padjadjaran for providing financial support through the Padjadjaran Excellence Fast Track Scholarship (Beasiswa Unggulan Pascasarjana Padjadjaran).

Authors' contributions

Muhammad Irfan Maulana conducted the study, collected and analysed the data, and drafted the manuscript. Indrawati Yudha Asmara reviewed and edited the manuscript. All authors contributed to drafting, reviewing, and approving the final manuscript.

Funding

Funding for this literature review was supported by Padjadjaran University through the Padjadjaran Excellence Fast Track Scholarship (Beasiswa Unggulan Pascasarjana Padjadjaran).

Competing interests

The authors declare that they have no competing interests.

Ethical considerations

All ethical issues, including plagiarism, consent to publish, study misconduct, data fabrication or falsification, duplicate publication or submission, and redundancy, have been carefully checked and confirmed by all authors prior to submission of this manuscript. The authors declare that no artificial intelligence (AI) tools were used for data analysis, study selection, interpretation of results, or scientific decision-making in this study. All processes, including literature screening, data extraction, thematic synthesis, and manuscript preparation, were conducted manually by the authors.

Availability of data and materials

All data and materials used in this study are derived from publicly accessible academic databases (Scopus, ScienceDirect, Google Scholar, and SINTA). No primary or proprietary data were collected.

REFERENCES

Abd-El Hamed AM, Abo-Gamil ZH, Elbarbary NK, Ghania AA, Fotouh A, and Darweish M (2025). A comparative study of performance and profitability measures for broilers raised in open and closed systems: Investigating the histopathological effects of heat stress during summer in Egypt. Open Veterinary Journal, 15(5): 2039-2048. DOI: https://www.doi.org/10.5455/OVJ.2025.v15.i5.20

Abiri R, Rizan N, Balasundram SK, Shahbazi AB, and Abdul-Hamid H (2023). Application of digital technologies for ensuring agricultural productivity. Heliyon, 9(12): e22601. DOI: https://www.doi.org/10.1016/j.heliyon.2023.e22601

Abo-Al-Ela HG, El-Kassas S, El-Naggar K, Abdo SE, Jahejo AR, and Al Wakeel RA (2021). Stress and immunity in poultry: Light management and nanotechnology as effective immune enhancers to fight stress. Cell Stress and Chaperones, 26(3): 457-472. DOI: https://www.doi.org/10.1007/s12192-021-01204-6

Adli DN, Fatyanosa TN, Al Huda F, Sholikin MM, and Sugiharto S (2025). Modelling the growth performance and thermal environment of broiler chicken houses via different machine learning algorithms assisted by a customized Internet of Things. Smart Agricultural Technology, 12: 101421. https://www.doi.org/10.1016/j.atech.2025.101421

Afeez N, Adeshina SA, Inci A, and Boukar MM (2019). A framework for poultry weather control with IoT in sub-Saharan Africa. 2019 15th International Conference on Electronics, Computer and Computation, pp. 1-6. DOI: https://www.doi.org/10.1109/ICECCO48375.2019.9043202

Ahmed MM, Hassanien EE, and Hassanien AE (2024). A smart IoT-based monitoring system in poultry farms using chicken behavioural analysis. Internet of Things, 25: 101010. DOI: https://www.doi.org/10.1016/j.iot.2023.101010

Aksjonov A and Kyrki V (2023). A safety-critical decision-making and control framework combining machine-learning-based and rule-based algorithms. SAE International Journal of Vehicle Dynamics, Stability, and NVH, arXiv:2201.12819 [cs.AI]. DOI: https://www.doi.org/10.48550/arXiv.2201.12819

Al-Chalabi DA, Ali AA, and Hussein FM (2017). Diagnostic environmental monitoring system in a poultry house. The Iraqi Journal of Agricultural Sciences, 48(3): 860-873. DOI: https://www.doi.org/10.36103/ijas.v48i3.399

Al-Doghman F, Moustafa N, Khalil I, and Zomaya AY (2023). AI-enabled secure microservices in edge computing: Opportunities and challenges. IEEE Transactions on Services Computing, 16(2): 1485-1504. DOI: https://www.doi.org/10.1109/TSC.2022.3155447

Alkhafaji M, Ramadan GM, Jaffer Z, and Jasim L (2024). Revolutionizing Agriculture: The Impact of AI and IoT. E3S Web of Conferences, 491: 01010. DOI: https://www.doi.org/10.1051/e3sconf/202449101010

Araújo GA, Bezerra SFC, and da Rocha AR (2024). Resource allocation based on task priority and resource consumption in edge computing. Journal of Internet Services and Applications, 15(1): 360-379. DOI: https://www.doi.org/10.5753/jisa.2024.4026

Azadeh A, Darivandi Shoushtari K, Saberi M, and Teimoury E (2014). An integrated artificial neural network and system dynamics approach in support of the viable system model to enhance industrial intelligence: The case of a large broiler industry. Systems Research and Behavioral Science, 31(2): 236-257. DOI: https://www.doi.org/10.1002/sres.2199

Barsagade AG and Rumale AS (2024). Internet of Things-based intelligent monitoring and controlling of poultry system using artificial intelligence. International Journal of Intelligent Systems and Applications in Engineering, 12(10s): 456-467. DOI: https://ijisae.org/index.php/IJISAE/article/view/4394

Beker A, Vanhooser SL, Swartzlander JH, and Teeter RG (2004). Atmospheric ammonia concentration effects on broiler growth and performance. Journal of Applied Poultry Research, 13(1): 5-9. DOI: https://www.doi.org/10.1093/japr/13.1.5

Belykh TI, Burdukovskaya Av, Ivonina OY, and Arkhipova Zv (2021). Microclimate influence investigation on broilers industrial production intensification by information technology methods. IOP Conference Series: Earth and Environmental Science, 839: 2044. DOI: https://www.doi.org/10.1088/1755-1315/839/3/032044

Bharanishree K, Dinesh KM, Jayashri, and Mugilan D (2025). Automated poultry farming using Internet of Things and machine learning. International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, pp. 492-496. DOI: https://www.doi.org/10.1109/ICEARS64219.2025.10940093

Bustamante E, García-Diego FJ, Calvet S, Estellés F, Beltrán P, Hospitaler A, and Torres AG (2013). Exploring ventilation efficiency in poultry buildings: The validation of computational fluid dynamics (CFD) in a cross-mechanically ventilated broiler farm. Energies, 6(5): 2605-2623. DOI: https://www.doi.org/10.3390/en6052605

Cai Y, Du X, Zhang C, and Li M (2025). ShieldDFL: A blockchain-based federated learning framework with dual privacy protection and reputation-driven consensus. IEEE Access, 13: 103931-103943. DOI: https://www.doi.org/10.1109/ACCESS.2025.3576261

Center for agricultural data and information systems (2024). Agricultural commodity outlook livestock subsector: Chicken meat. Secretariat General of the Ministry of Agriculture Indonesia, pp. 12-13. Available at: https://satudata.pertanian.go.id/assets/docs/publikasi/Outlook_Daging_Ayam_2024.pdf

Chen L, Fabian-Wheeler EE, Cimbala JM, Hofstetter D, and Patterson P (2021). Computational fluid dynamics analysis of alternative ventilation schemes in cage-free poultry housing. Animals, 11(8): 2352. DOI: https://www.doi.org/10.3390/ani11082352

Chen R, Meng Q, and Yu JJ (2023). Optimal government incentives to improve the new technology adoption: Subsidizing infrastructure investment or usage?. Omega, 114: 102740. DOI: https://www.doi.org/10.1016/j.omega.2022.102740

Chojer H, Branco PTBS, Martins FG, Alvim-Ferraz MCM, and Sousa SIV (2022). Can data reliability of low-cost sensor devices for indoor air particulate matter monitoring be improved? – An approach using machine learning. Atmospheric Environment, 286: 119251. DOI: https://www.doi.org/10.1016/j.atmosenv.2022.119251

Costantino A, Fabrizio E, Villagrá A, Estellés F, and Calvet S (2020). The reduction of gas concentrations in broiler houses through ventilation: Assessment of the thermal and electrical energy consumption. Biosystems Engineering, 199: 135-148. https://www.doi.org/10.1016/j.biosystemseng.2020.01.002

Curi TMRC, Conti D, Vercellino RdoA, Massari JM, de Moura DJ, de Souza ZM, and Montanari R (2017). Positioning of sensors for control of ventilation systems in broiler houses: A case study. Scientia Agricola, 74(2): 101-109. DOI: https://www.doi.org/10.1590/1678-992X-2015-0369

da Silva CT, Junior TY, de Bettio RW, and Bahuti M (2025). Design of wireless web-based multiplatform system for thermal environmental control of broiler facilities using fuzzy set theory. Anais da Academia Brasileira de Ciências, 97(1): e20240032. DOI: https://www.doi.org/10.1590/0001-3765202520240032

De Vito S, Castaldo A, Loffredo F, and Di Francia G (2007). Gas concentration estimation in ternary mixtures with room temperature operating sensor array using tapped delay architectures. Sensors and Actuators B: Chemical, 124(2): 309-316. DOI: https://www.doi.org/10.1016/j.snb.2006.12.039

Debauche O (2020). Edge computing and artificial intelligence for real-time poultry monitoring. International workshop on artificial intelligence & Internet of Things (A2IoT), Leuven, Belgium. Procedia Computer Science, 175: 534-541. DOI: https://www.doi.org/10.1016/j.procs.2020.07.076

Detsch DT, Conti D, Diniz-Ehrhardt MA, and Martínez JM (2018). On the controlling of temperature: A proposal for a real-time controller in broiler houses. Scientia Agricola, 75(6): 445-451. https://www.doi.org/10.1590/1678-992x-2016-0456

Dozier III WA, Purswell JL, and Branton SL. (2006). Growth responses of male broilers subjected to high air velocity for either twelve or twenty-four hours from thirty-seven to fifty-one days of age. The Journal of Applied Poultry Research, 15(3): 362-366. https://doi.org/10.1093/japr/15.3.362

Drewry JL, Mondaca MR, Luck BD, and Choi CY (2017). A computational fluid dynamics model of a dairy holding area [Paper]. ASABE annual international meeting, Spokane, WA. American Society of Agricultural and Biological Engineers, 1701658. DOI: https://www.doi.org/10.13031/aim.201701658

Drgoňa J, Picard D, Kvasnica M, and Helsen L (2018). Approximate model predictive building control via machine learning. Applied Energy, 218: 199-216. DOI: https://www.doi.org/10.1016/j.apenergy.2018.02.156

Du L, Yang C, Dominy R, Yang L, Hu C, Du H, Li Q, Yu C, Xie L, and Jiang X (2019). Computational fluid dynamics aided investigation and optimization of a tunnel-ventilated poultry house in China. Computers and Electronics in Agriculture, 159: 1-15. DOI: https://www.doi.org/10.1016/j.compag.2019.02.020

Elango MK, Harini A, Soundar R, and Suroopa P (2024). AI-based digital disease recognition using collaborative conveyor machine for poultry farming. IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), pp. 1716-1721. DOI: https://www.doi.org/10.1109/IC2PCT60090.2024.10486780

Fahrurrozi I, Wahyono S, Sari Y, Sari AK, Usuman I, and 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): 1283-1292. DOI: https://www.doi.org/10.11591/ijeecs.v33.i2.pp1283-1292

Faridah, Utami SS, Yanti RJ, and Wijaya R (2021). Optimal thermal sensors placement based on indoor thermal environment characterization by using CFD model. Journal of Applied Engineering Science, 19(3): 628-641. DOI: https://www.doi.org/10.5937/jaes0-28985

Fathurohman MAA, Sumitra ID, and Daud AR (2023). Integration of wireless sensor network and IoT for enhanced broiler closed-house monitoring: A case study at broiler teaching farm. 9th International Conference on Signal Processing and Intelligent Systems (ICSPIS), pp. 1-8. DOI: https://www.doi.org/10.1109/ICSPIS59665.2023.10402746

Finistrosa R, Mañoso C, de Madrid ÁP, and Romero M (2025). Low-cost IoT and LoRaWAN-based system for laying hen identification in family poultry farms. Applied Sciences, 15(9): 4856. DOI: https://www.doi.org/10.3390/app15094856

George AS and Hovan George AS (2023). Optimizing poultry production through advanced monitoring and control systems. Partners Universal International Innovation Journal, 1(5): 77-97. DOI: https://www.doi.org/10.5281/zenodo.10050352

Ghandi IK. (2023). AIoT-driven edge computing for rural small-scale poultry farming: Smart environmental monitoring and anomaly detection for enhanced productivity. International Journal on Recent and Innovation Trends in Computing and Communication, 11(8): 44-52. DOI: https://www.doi.org/10.17762/ijritcc.v11i8.7923

Ghasemi K, Oishique ST, Tasnim SH, Sokolowski M, Gorji-Bandpy T, and Mahmud S (2025). Operational performance of ventilation mechanisms for layer houses: Modeling with experimental validation. Computers and Electronics in Agriculture, 238: 110818. DOI: https://www.doi.org/10.1016/j.compag.2025.110818

Gowri R, Ilakkiyalakshmi S, Rathipriya K, and Naveenkumar S (2023). IoT-based poultry farm monitoring system with deep learning techniques. 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), pp. 963-966. DOI: https://www.doi.org/10.1109/ICIMIA60377.2023.10425921

Guo Y, Wang J, Lin P, and Han Y (2025). Multiple behaviour recognition of free-range broilers in cross-domain scenarios using MCA-YOLOv5. Biosystems Engineering, 257: 104226. DOI: https://www.doi.org/10.1016/j.biosystemseng.2025.104226

Hambali HFH, Patchmuthu RK, and Wan AT (2020). IoT-based smart poultry farm in Brunei. 8th International Conference on Information and Communication Technology (ICoICT), pp. 1-5. DOI: https://www.doi.org/10.1109/ICoICT49345.2020.9166331

Harrouz JP, Katramiz E, Ghali K, Ouahrani D, and Ghaddar N (2021). Comparative analysis of sustainable desiccant – Evaporative based ventilation systems for a typical Qatari poultry house. Energy Conversion and Management, 245: 114556. DOI: https://www.doi.org/10.1016/j.enconman.2021.114556

Haseeb S, Hashim AHA, Khalifa OO, and Ismail AF (2017). Connectivity, interoperability and manageability challenges in internet of things. AIP Conference Proceedings, 1883: 020004. DOI: https://www.doi.org/10.1063/1.5002022

Heymsfield C, Liang Y, and Costello TA (2018). Computational fluid dynamics model for air velocity through a poultry transport trailer in a holding shed. Proceedings of the 10th International Livestock Environment Symposium (ILES), 36(6): 963-973. DOI: https://www.doi.org/10.13031/iles.ILES18-005

Husein J and Kharisma OB (2020). Internet of Things (IOT) development for the chicken coop temperature and humidity monitoring system based on fuzzy. Indonesian Journal of Artificial Intelligence and Data Mining, 3(1): 9-20. DOI: https://www.doi.org/10.24014/ijaidm.v3i1.9294

Ibrahima KA and Cissé A (2022). Air quality remote monitoring module: I4.0 application in smart poultry farm. In: M. Hamlich, L. Bellatreche, A. Siadat, S. Ventura (Editors.), Smart applications and data analysis. SADASC 2022. Communications in Computer and Information Science, 1677: 339-347. DOI: https://www.doi.org/10.1007/978-3-031-20490-6_27

Jabade V, Mhetre MB, Mali PP, and Mor AG (2024). IoT-based smart poultry farm and fish farming system. 1st International Conference on Innovative Sustainable Technologies for Energy, Mechatronics, and Smart Systems (ISTEMS), pp. 1-6. DOI: https://www.doi.org/10.1109/ISTEMS60181.2024.10560208

Jebari H, Hayani Mechkouri M, Rekiek S, and Reklaoui K (2023). Poultry-edge-AI-IoT system for real-time monitoring and predicting by using artificial intelligence. International Journal of Interactive Mobile Technologies, 17(12): 149-170. DOI: https://www.doi.org/10.3991/ijim.v17i12.38095

Jia Z, Wu K, Wang H, and Liang D (2024). An improved crop yield prediction using CNN-BiLSTM model with attention mechanism. Journal of the ASABE, 67(6): 1459-1467. DOI: https://www.doi.org/10.13031/ja.15629

Jongbo A (2019). Investigation into an alternative approach of environmental control to enhance sensible heat transfer from broiler chickens during hot weather periods. Thesis. Harper Adams University, United Kingdom. Available at: https://hau.repository.guildhe.ac.uk/id/eprint/17474/1/Ayoola%20Jongbo.pdf

Kaukonen E, Norring M, and Valros A (2016). Effect of litter quality on foot pad dermatitis, hock burns and breast blisters in broiler breeders during the production period. Avian Pathology, 45(6): 667-673. DOI: https://www.doi.org/10.1080/03079457.2016.1197377

Kiruthika R, Sahoo SK, Vathani BS, Reddy GR, Rajanarayanan S, and Prakash S (2024). Predictive modelling of poultry growth optimization in IoT-connected farms using SVM for sustainable farming practices. 10th International Conference on Communication and Signal Processing (ICCSP), pp. 677-682. DOI: https://www.doi.org/10.1109/ICCSP60870.2024.10543463

Küçüktopçu E, Cemek B, and Simsek H (2024). Modeling environmental conditions in poultry production: Computational fluid dynamics approach. Animals, 14(3): 501. DOI: https://www.doi.org/10.3390/ani14030501

Laknizi A, Mahdaoui M, ben Abdellah A, Anoune K, Bakhouya M, and Ezbakhe H (2019). Performance analysis and optimal parameters of a direct evaporative pad cooling system under the climate conditions of Morocco. Case Studies in Thermal Engineering, 13: 100362. DOI: https://www.doi.org/10.1016/j.csite.2018.11.013

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

Lee IB, Sase S, and Sung SH (2007). Evaluation of CFD accuracy for the ventilation study of a naturally ventilated broiler house. Japan Agricultural Research Quarterly, 41(1): 53-64. DOI: https://www.doi.org/10.6090/jarq.41.53

Li DC, Huang CT, Tseng CW, and Chou LD (2021). Fuzzy-based microservice resource management platform for edge computing in the Internet of Things. Sensors, 21(11): 3800. DOI: https://www.doi.org/10.3390/s21113800

Liani YA, Munthe IR, Irmayani D, Broto BE, Yanris GJ, Prasetya DA, Haryanto R, Adi PD, Muslikh AR, and Arifuddin R (2021). The broiler chicken coop temperature monitoring use fuzzy logic and LoRaWAN. 3rd International Conference on Electronics Representation and Algorithm (ICERA), pp. 161-166. DOI: https://www.doi.org/10.1109/ICERA53111.2021.9538771

Lillahulhaq Z, Widodo WA, Sutardi, Hakim L, and Nugroho A (2024). Improving poultry system in close house cage through advanced HVAC design: A review of evaporative cooling pads and energy efficiency in broiler cages. Mechanical Engineering for Society and Industry, 4(3): 368-387. DOI: https://www.doi.org/10.31603/mesi.12689

Mahmood MH, Sultan M, Miyazaki T, Koyama S, and Maisotsenko VS (2016). Overview of the Maisotsenko cycle–A way towards dew point evaporative cooling. Renewable and sustainable energy reviews, 66: 537-555. DOI: https://www.doi.org/10.1016/j.rser.2016.08.022

Morozova M (2024). Methodology for controlling greenhouse microclimate parameters and yield forecast using neural network technologies. In: V. Eremenko and A. Zaporozhets (Editors), Advanced information-measuring technologies and systems I, pp. 1-7. DOI: https://www.doi.org/10.1007/978-3-031-40718-5_7

Mulling L, Cleber L, and Seiji OM (2023). Calibration of a metal oxide sensor for ammonia detection targeting IoT solutions. Brazilian Symposium on Computing System Engineering, SBESC, pp. 1-6. DOI: https://www.doi.org/10.1109/SBESC60926.2023.10324290

Nalendra KA and Waspada HP (2021). Application of artificial intelligence for temperature and humidity control in broiler cages based on the Internet of Things. Generation Journal, 5(2): 59-68. DOI: https://www.doi.org/10.29407/gj.v5i2.15706

Nuanmeesri S and Poomhiran (2020). Developing of intelligence walking stick and mobile application for elderly health care using the Internet of Things. International Journal of Interactive Mobile Technologies, 14(14): 4-15. DOI: https://www.doi.org/10.3991/ijim.v14i14.14813

Oke OE, Akosile OA, Uyanga VA, Oke FO, Oni AI, Tona K, and Onagbesan OM (2024). Climate change and broiler production. Veterinary Medicine and Science, 10(3): e1416. DOI: https://www.doi.org/10.1002/vms3.1416

Oliveira F, Pereira P, Dantas J, Araujo J, and Maciel P (2024). Dependability evaluation of a smart poultry house: Addressing availability issues through the edge, fog, and cloud computing. IEEE Transactions on Industrial Informatics, 20(2): 1304-1312. DOI: https://www.doi.org/10.1109/TII.2023.3275656

Pakage S, Hartono B, Fanani Z, Nugroho BA, Iyai DA, Palulungan JA, and Nurhayati OD (2020). Performance measurement of broiler production in closed house systems and open house systems in Malang Regency, East Java, Indonesia. Indonesian Journal of Animal Husbandry Science, 15(4): 383-389. Available at: https://ejournal.unib.ac.id/jspi/article/view/12257

Pereira WF, Fonseca LDS, Putti FF, and Naves LDP (2020). Environmental monitoring in a poultry farm using an instrument developed with the Internet of Things concept. Computers and Electronics in Agriculture, 170: 105257. DOI: https://www.doi.org/10.1016/j.compag.2020.105257

Postolache S, Sebastião P, Viegas V, and Postolache O (2025). Digital twin for horticulture farm: Data source and data domain architecture [Instrumentation and Measurement Systems]. IEEE Instrumentation & Measurement Magazine, 28(4): 22-30. DOI: https://www.doi.org/10.1109/MIM.2025.11021356

Potdukhe N, Gourshettiwar P, Zade S, and Waghale A (2025). Blockchain-enabled federated learning systems with explainable AI: A review. Proceedings of the 2nd International Conference on Machine Learning and Autonomous Systems (ICMLAS), pp. 1650-1656. DOI: https://www.doi.org/10.1109/ICMLAS64557.2025.10968523

Pourvosoghi N, Nikbakht AM, Sharifian F, and Najafi R (2018). Numerical analyses of air velocity and temperature distribution in poultry house using computational fluid dynamics. INMATEH – Agricultural Engineering, 55(2): 81-90. DOI: https://www.doi.org/10.35633/inmateh-55-09

Prangon NF and Wu J (2024). AI and computing horizons: Cloud and edge in the modern era. Journal of Sensor and Actuator Networks, 13(4): 44. DOI: https://www.doi.org/10.3390/jsan13040044

Priyanka K, Sridhara N, Prasanna Kumar MJ, and Vijay Kumar MS (2023). IoT-driven transformation of poultry farming: Ensuring health, hygiene, and efficiency. Proceedings of the International Conference on Recent Advances in Science and Engineering

Technology (ICRASET), pp. 1-5. DOI: https://www.doi.org/10.1109/ICRASET59632.2023.10420195

Rahaman M, Lin CY, Pappachan P, and Hsu CH (2024). Privacy-centric AI and IoT solutions for smart rural farm monitoring and control. Sensors, 24(13): 4157. DOI: https://www.doi.org/10.3390/s24134157

Reddy PCP, Prabaharan S, Rajaram P, and Ebenezer SS (2024). Smart poultry farming: CNN-driven environmental optimization for sustainability. International Conference on Distributed Systems, Computer Networks and Cybersecurity (ICDSCNC), pp. 1-9. DOI: https://www.doi.org/10.1109/ICDSCNC62492.2024.10939551

Revanth M, Sanjeev Kumar K, Srinivasan M, Stonier AA, and Vanaja DS (2021). Design and development of an IoT-based smart poultry farm. 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), pp. 1-4. DOI: https://www.doi.org/10.1109/ICAECA52838.2021.9675553

Ribeiro R, Casanova D, Teixeira M, Wirth B, Heitor M Gomesc, André PB, and Enembreckc F (2019). Generating action plans for poultry management using artificial neural network. Computers and Electronics in Agriculture, 161: 131-140. DOI: https://www.doi.org/10.1016/j.compag.2018.02.017

Rosmasari R, Prafanto A, and Firdaus M (2025). Implementation of naïve Bayes Gaussian algorithm for real-time classification of broiler cage conditions. Journal of Applied Data Sciences, 6(3): 1551-1562. DOI: https://www.doi.org/10.47738/jads.v6i3.694

Sädeharju S (2025). The elements of intuition in decision-making: A multidimensional framework based on Finnish regenerative farmers' experiences. Journal of Rural Studies, 117. DOI: https://www.doi.org/10.1016/j.jrurstud.2025.103656.

Safputra A, Kamelia L, Zaki Hamidi EA, and Endy (2023). IoT-based monitoring and feeder control for smart poultry farm system. 2023 9th International Conference on Wireless and Telematics (ICWT), pp. 1-4. DOI: https://www.doi.org/10.1109/ICWT58823.2023.10335335

Saifullah S (2025). Comparative analysis of long short-term memory and gated recurrent unit models for chicken egg fertility classification using deep learning. Engineering Proceedings, 87(1): 7. DOI: https://www.doi.org/10.3390/engproc2025087007

Saner KA and Shekhawat SP (2023). Design and analysis of ventilation system for closed poultry house in tropical climate conditions. Journal of World's Poultry Research, 13(3): 323-331. DOI: https://www.doi.org/10.36380/jwpr.2023.35

Saner KA and Shekhawat SP (2022). Mathematical modelling of ventilation system for closed poultry house in tropical climate conditions. International Journal of Mechanical Engineering, 7(4): 81-86. Available at: https://kalaharijournals.com/resources/APRIL10.pdf

Sans ECO, Vale MM, Vieira FMC, Vismara ES, and Molento CFM (2021). In-barn heterogeneity of broiler chicken welfare in two industrial house designs and two seasons in Southern Brazilian subtropical climate. Livestock Science, 250: 104569. DOI: https://www.doi.org/10.1016/j.livsci.2021.104569

Saraz JAO, Rocha KSO, Damasceno FA, Tinoco IFF, Osorio R, and Tobón JCA (2017). A CFD approach to assess the effects of different opening combinations in poultry houses. Revista Brasileira de Engenharia Agricola e Ambiental, 21(12): 852-857. DOI: https://www.doi.org/10.1590/1807-1929/agriambi.v21n12p852-857

Sarbishei O, Fekr AR, Janidarmian M, and Radecka K (2013). A minimum MSE sensor fusion algorithm with tolerance to multiple faults. Proceedings of the 18th IEEE European Test Symposium (ETS). DOI: https://www.doi.org/10.1109/ETS.2013.6569380

Setiadi R, Munadi, and Tauviqirrahman M (2018). Numerical analysis for temperature profile of the closed house using computational fluid dynamics. AIP Conference Proceedings, 1941: 020032. https://www.doi.org/10.1063/1.5028090

Shahzad K, Sultan M, Bilal M, Ashraf H, Farooq M, Miyazaki T, Sajjad U, Ali I, and Hussain MI (2021). Experiments on energy-efficient evaporative cooling systems for poultry farm application in Multan (Pakistan). Sustainability, 13(5): 2836. DOI: https://www.doi.org/10.3390/su13052836

Slayi M, Zhou L, and Jaja IF (2023). Constraints inhibiting farmers' adoption of cattle feedlots as a climate-smart practice in rural communities of the Eastern Cape, South Africa: An in-depth examination. Sustainability, 15(20): 14813. DOI: https://www.doi.org/10.3390/su152014813

Sukri H, Adiputra F, Basuki A, Syamsuddin AA, and Aziz A (2023). K-nearest neighbor method approach in implementing automatic feeding efficiency based on the Internet of Things in broiler chickens. IEEE 9th Information Technology International Seminar (ITIS), pp. 1-6. DOI: https://www.doi.org/10.1109/ITIS59651.2023.10420176

Suresh ML, Rani SB, Rao TKRK, and Slimane JB (2025). A hybrid convolutional neural network-temporal attention mechanism approach for real-time prediction of soil moisture and temperature in precision agriculture. International Journal of Advanced Computer Science and Applications, 16(5): 2025. DOI: http://www.dx.doi.org/10.14569/IJACSA.2025.0160556

Swelum AA, El-Saadony MT, Abd El-Hack ME, Ghanima MMA, Shukry M, Alhotan RA, Hussein EOS, Suliman GM, Ba-Awadh H, Ammari AA et al. (2021). Ammonia emissions in poultry houses and microbial nitrification as a promising reduction strategy. Science of the Total Environment, 781: 146978. DOI: https://www.doi.org/10.1016/j.scitotenv.2021.146978

Syahrorini S, Rifai A, Saputra DHR, and Ahfas A (2020). Design smart chicken cage based on Internet of Things. IOP Conference Series: Earth and Environmental Science, 519(1): 012014. DOI: https://www.doi.org/10.1088/1755-1315/519/1/012014

Tainika B, Şekeroğlu A, Akyol A, and Waithaka Ng'ang'a Z (2023). Welfare issues in broiler chickens: An overview. World's Poultry Science Journal, 79(2): 285-329. DOI: https://www.doi.org/10.1080/00439339.2023.2175343

Taleb HM, Mahrose K, Abdel-Halim AA, and Abd El-Hack ME (2025). Using artificial intelligence to improve poultry productivity: A review. Annals of Animal Science, 25(1): 23-33. DOI: https://www.doi.org/10.2478/aoas-2024-0039

Tambunan IH and Apryanto NR (2024). Prototyping an IoT-based smart controlled poultry farm system. Proceedings 2nd International Conference on Technology Innovation and Its Applications, ICTIIA, pp. 1-5. DOI: https://www.doi.org/10.1109/ICTIIA61827.2024.10761605

Teng GH (2015). Information sensing and environment control of precision facility livestock and poultry farming. Smart Agriculture, 1(3): 1-12. DOI: https://www.doi.org/10.12133/j.smartag.2019.1.3.201905-SA006

Trane M, Ricciardi G, Scalas M, and Ellena M (2023). From CFD to GIS: A methodology to implement urban microclimate georeferenced databases. TECHNE Journal of Technology for Architecture and Environment, 25: 124-133. DOI: https://www.doi.org/10.36253/techne-13661

Ullah I, Khan IU, Ouaissa M, Ouaissa M, and Hajjami SE (2024). Future communication systems using artificial intelligence, Internet of Things and data science, 1st Edition. CRC Press, pp. 1-252. DOI: https://www.doi.org/10.1201/9781032648309

Utomo GP, Munadi M, and Tauviqirrahman M (2019). Design and development of broiler feeding system for chicken model closed-house system. International Journal of Recent Technology and Engineering, 8(2): 4842-4846. DOI: https://wwww.doi.org/10.35940/ijrte.B3453.078219

Umapathi N, Shivani K, Prakash MA, and Soundararajan C (2025). IoT-based smart animal health monitoring system. In: R. P. Mahapatra, S. K. Peddoju, and S. Karthick (Editors), Proceedings of International Conference on Recent Trends in Computing, 885: 31. DOI: https://www.doi.org/10.1007/978-981-97-8836-1_31

Vuka E and Wu Y (2024). What is stopping digital agricultural production technologies from farmers. IEEE 24th International Symposium on Computational Intelligence and Informatics (CINTI), Budapest, Hungary, pp. 179-184. DOI: https://www.doi.org/10.1109/CINTI63048.2024.10830897

Wah JNK (2025). The role of AI in transforming agriculture: Toward sustainable growth in an era of climate change. Scientific Culture, 11(2): 45-63. DOI: https://www.doi.org/10.5281/zenodo.15587933

Wasti S, Sah N, and Mishra B (2020). Impact of heat stress on poultry health and performances, and potential mitigation strategies. Animals, 10(8): 1266. DOI: https://www.doi.org/10.3390/ani10081266

Wheeler EF, Zajaczkowski JL, and Sabeh NC (2003). Field evaluation of temperature and velocity uniformity in tunnel and conventional ventilation broiler houses. Applied Engineering in Agriculture, 19(3): 367-377. DOI: https://www.doi.org/10.13031/2013.13665

Wicaksono D, Perdana D, and Mayasari R (2017). Design and analysis of automatic temperature control in the broiler poultry farm based on wireless sensor network. 2nd International Conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE), pp. 450-455. DOI: https://www.doi.org/10.1109/ICITISEE.2017.8285549

Xin H, Berry IL, Abler GTOT, and Ostello TAC (2017). Heat and moisture production of poultry and their housing systems: Broilers. Trans ASAE, 44: 1851-1857. DOI: https://www.doi.org/10.13031/2013.7023

Yang S, Yu X, and Zhou Y (2020). LSTM and GRU neural network performance comparison study: Taking Yelp review dataset as an example. Proceedings of the 2020 International Workshop on Electronic Communication and Artificial Intelligence (IWECAI), pp. 98-101. DOI: https://www.doi.org/10.1109/IWECAI50956.2020.00027

Yang X, Zhang F, Jiang T, and Yang D (2019). Environmental monitoring of chicken house based on edge computing in Internet of Things. Proceedings IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), pp. 617-620. DOI: https://www.doi.org/10.1109/ITAIC.2019.8785634

Zanchi M, Zapperi S, and La Porta CAM (2024). Optimized placement of sensor networks by machine learning for microclimate evaluation. Computers and Electronics in Agriculture, 225: 109305. DOI: https://www.doi.org/10.1016/j.compag.2024.109305

Zarzycki K and Ławryńczuk M (2021). LSTM and GRU neural networks as models of dynamical processes used in predictive control: A comparison of models developed for two chemical reactors. Sensors, 21(16): 5625. DOI: https://www.doi.org/10.3390/s21165625

Zhang P, Dong W, and Gao D (2014). An optimal method of data fusion for multi-sensors based on Bayesian estimation. Chinese Journal of Sensors and Actuators, 27(5): 643-648. https://www.doi.org/10.3969/j.issn.1004-1699.2014.05.014