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

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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,

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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.

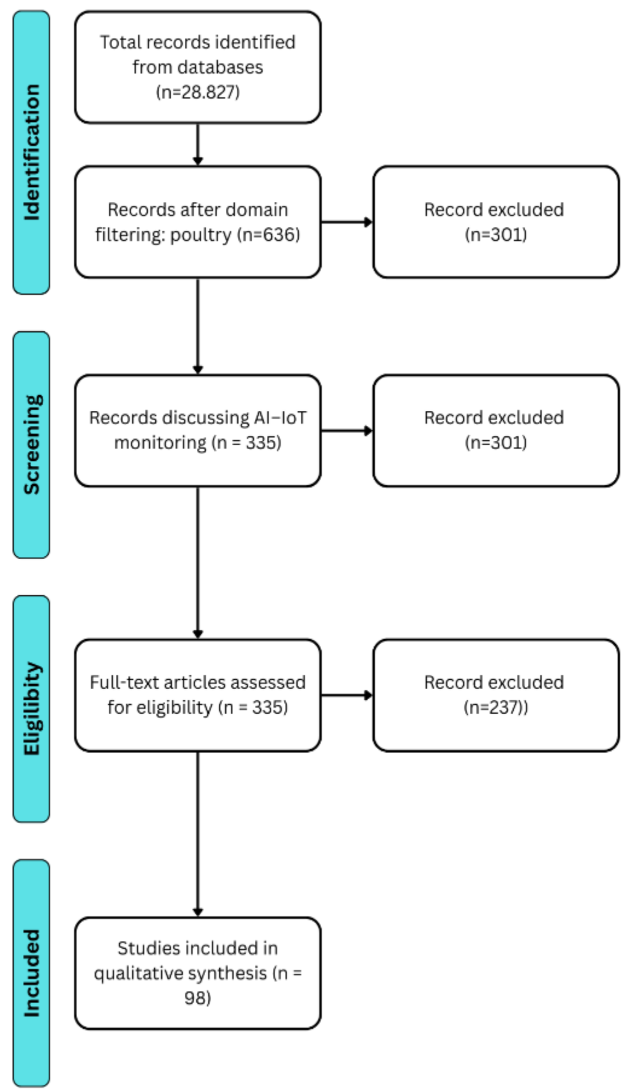

Figure 1. The PRISMA flow diagram for choosing the articles in this study

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).

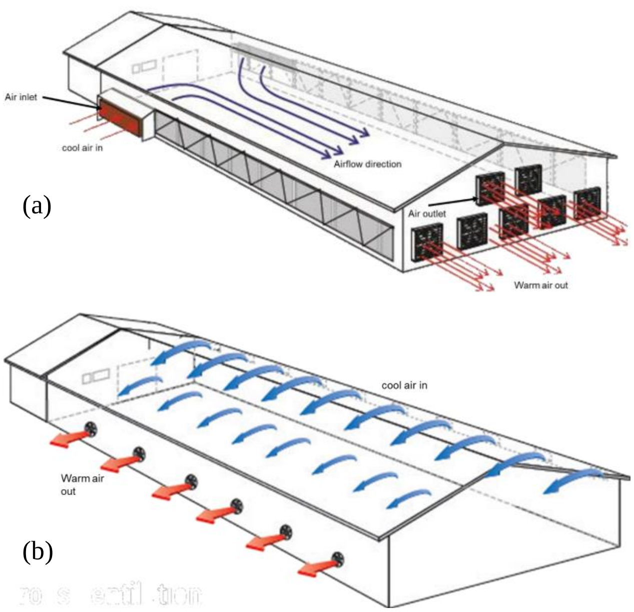

Figure 2. Schematic comparison of tunnel **(a)** and cross **(b)** ventilation in closed house systems. Source: Jongbo (2020).

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.

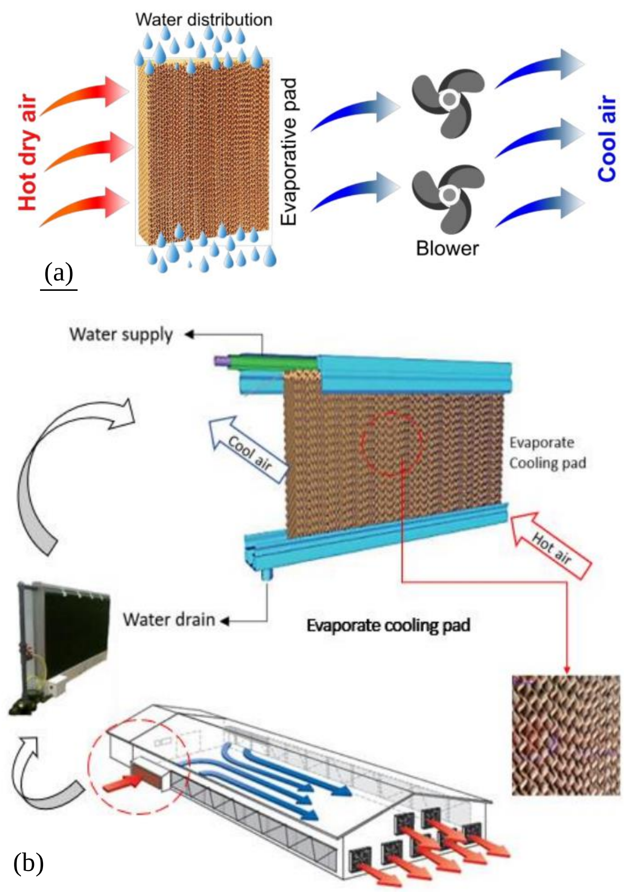

Figure 3. Working mechanism of evaporative cooling pads in closed house systems. Sources: **(a)** Shahzad et al., 2021; **(b)** Lillahulhaq et al., 2024.

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).

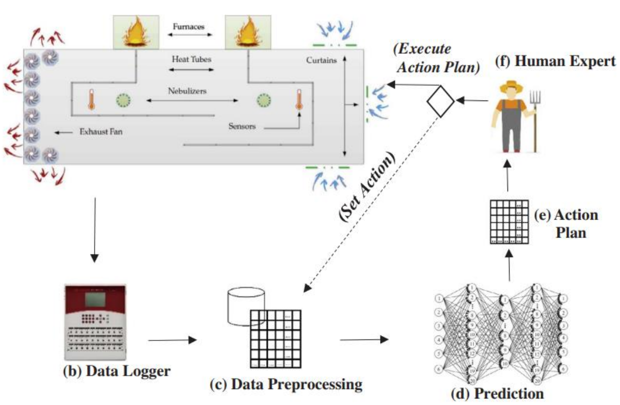

Figure 4. The learning model structure of neural networks. Source: Ribeiro (2019).

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

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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.

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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.

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