

Design and Implementation of an AI-IoT Integrated Cloud Platform for Real-Time Poultry Environmental Monitoring and Decision Support

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DOI: <https://dx.doi.org/10.51584/IJRIAS.2026.11010037>

Received: 12 January 2026; Accepted: 19 January 2026; Published: 31 January 2026

ABSTRACT

The rapid digitalisation of livestock production systems has intensified the demand for affordable, scalable, and user-accessible smart farming solutions, particularly in poultry management, where environmental conditions directly influence animal welfare and productivity. This study presents the design, implementation, and real-world deployment of an AI-IoT integrated cloud platform for real-time poultry environmental monitoring and decision support. The proposed system integrates low-cost IoT sensor nodes for temperature, humidity, and ammonia monitoring, along with energy-efficient sleep scheduling mechanisms and machine-learning-based predictive analytics. Environmental data acquired by distributed sensor nodes is transmitted via Wi-Fi to a central processing unit and securely uploaded to the cloud, where it is stored, analysed, and visualised through an interactive Streamlit dashboard. A hybrid Random Forest–Support Vector Classifier model was employed to provide predictive insights into environmental risk conditions, enabling proactive intervention beyond conventional threshold-based alerts. The platform was deployed and evaluated in a real poultry farm environment, demonstrating reliable real-time monitoring, low-latency cloud connectivity, and improved environmental stability. Practical outcomes include enhanced decision-making for non-technical users, improved accessibility via an intuitive web interface, and measurable reductions in environmental stress indicators associated with poultry mortality. The results confirm the system's effectiveness in democratising smart poultry farming and highlight its scalability potential for broader multi-livestock and precision agriculture applications.

Keywords: Internet of Things (IoT); cloud computing; Streamlit dashboard; smart farming; environmental monitoring; poultry management; machine learning; decision support systems.

INTRODUCTION

The global poultry industry is undergoing a significant transformation driven by rapid advances in digital technologies, increasing demand for animal protein, and heightened concerns about sustainability, animal welfare, and production efficiency. Poultry production systems are susceptible to micro-environmental conditions such as temperature, relative humidity, and air quality, which directly influence bird health, feed conversion efficiency, and mortality rates (Xin et al., 2021; Zhang et al., 2022). In tropical and developing regions in particular, environmental instability and limited access to skilled farm management exacerbate production losses, underscoring the need for intelligent and accessible monitoring solutions.

Conventional poultry farm management relies heavily on manual observation and static control mechanisms, including periodic measurement of environmental parameters and threshold-based actuation of ventilation or cooling systems. These approaches are labour-intensive, prone to human error, and unable to respond promptly to transient or progressive environmental changes (Wang et al., 2021). Moreover, traditional systems provide limited historical insight and virtually no predictive capability, restricting farmers to reactive decision-making rather than proactive environmental control. As poultry production scales in size and complexity, such limitations increasingly constrain productivity and sustainability.

The emergence of the Internet of Things (IoT) has enabled continuous, real-time acquisition of environmental data through distributed sensor networks, while cloud computing provides scalable storage, processing, and remote accessibility of farm data (Liakos et al., 2018; Gupta et al., 2020). When combined with machine learning (ML), IoT systems can move beyond simple monitoring to deliver predictive analytics, early warning systems, and data-driven decision support (Kamilaris & Prenafeta-Boldú, 2018). Despite these advances, several existing smart poultry solutions remain expensive, energy-inefficient, technically complex, or inaccessible to non-technical users, particularly in resource-constrained settings (Gill et al., 2022).

Another critical challenge in IoT-based livestock monitoring is energy consumption. Continuous sensing and wireless communication significantly reduce battery life, increasing maintenance costs and limiting the long-term feasibility of deployment (Boursianis et al., 2022). While energy-efficient sleep scheduling techniques have been proposed, countless implementations compromise data accuracy or system responsiveness, reducing their suitability for dynamic poultry environments (Guo et al., 2021). Additionally, most deployed systems rely on static threshold-based alerts, which fail to capture complex interactions among environmental variables or anticipate gradual risk escalation.

In response to these challenges, this study aims to develop a cloud-integrated AI–IoT framework that combines real-time environmental monitoring, energy-efficient operation, predictive machine learning analytics, and an intuitive visualisation interface. The primary objective is to design and implement an affordable, scalable platform that enables poultry farmers (regardless of technical expertise) to monitor environmental conditions, receive actionable insights, and make informed real-time decisions. The system leverages low-cost sensing hardware, hybrid machine learning models, and a Streamlit-based web dashboard to bridge the gap between advanced analytics and practical farm-level usability.

The key contributions of this work are threefold. First, it presents the design of an end-to-end IoT architecture integrating environmental sensing, wireless data transmission, cloud storage, and real-time visualisation. Second, it introduces a user-friendly Streamlit dashboard that translates complex sensor data and machine learning outputs into intuitive visual insights for non-technical users. Third, it demonstrates the practical effectiveness of the proposed platform through real-world deployment in a poultry farm, highlighting improvements in environmental stability, accessibility, and decision support. Collectively, these contributions situate the proposed system as a viable pathway toward democratising smart poultry farming and advancing precision livestock management in both developed and developing regions.

Related Works

The integration of Internet of Things (IoT), cloud computing, and artificial intelligence has received increasing research attention in the domain of smart agriculture, with poultry farming emerging as a critical application area due to its sensitivity to environmental conditions. Existing studies generally focus on three major themes: IoT-based environmental monitoring platforms, machine-learning–driven analytics for livestock management, and cloud-based visualisation and decision-support systems.

Early IoT-driven poultry monitoring systems primarily emphasised real-time sensing and threshold-based control of environmental parameters such as temperature, humidity, and air quality. Liakos et al. (2018) highlighted the foundational role of sensor networks in precision agriculture, noting their effectiveness in continuous environmental data acquisition but also identifying limitations related to system scalability and energy consumption. Similarly, Pereira et al. (2020) demonstrated that IoT-enabled environmental monitoring could significantly reduce heat stress incidents in poultry houses by enabling timely ventilation control. However, such systems primarily relied on static threshold logic, limiting their capacity to anticipate gradual or compound environmental risks.

In order to address these limitations, recent studies have incorporated machine learning techniques into IoT-based livestock monitoring frameworks. Kamilaris and Prenafeta-Boldú (2018) and Zhang et al. (2021) showed that supervised learning models, including Random Forest and Support Vector Machines, can effectively model nonlinear relationships among environmental variables and predict adverse conditions. In poultry-specific contexts, Ojo et al. (2022) reported that Random Forest classifiers achieved high accuracy in classifying environmental risk states when trained on historical datasets of temperature, humidity, and ammonia. Despite

these promising results, many machine learning-enabled systems remain computationally demanding and are often evaluated offline, limiting their applicability for real-time farm operations.

Energy efficiency has emerged as another critical concern in IoT-based agricultural deployments. Continuous sensing and wireless transmission significantly increase power consumption, especially in Wi-Fi-based systems commonly used in small and medium-scale farms. Guo et al. (2021) and Boursianis et al. (2022) proposed adaptive sleep scheduling and low-power communication strategies to extend the lifetime of sensor nodes. While these approaches demonstrate substantial energy savings, they often introduce trade-offs between data resolution, responsiveness, and implementation complexity. Moreover, few studies integrate energy-aware operation

multi-farm management and long-term performance analysis. Nonetheless, many existing platforms with intelligent analytics in a unified poultry monitoring framework.

Cloud computing has further expanded the capabilities of smart agriculture platforms by enabling centralised data storage, scalable analytics, and remote accessibility. Gupta et al. (2020) and Gill et al. (2022) emphasised that cloud-integrated IoT systems facilitate rely on proprietary dashboards or complex interfaces that hinder adoption by non-technical users, particularly in developing regions. Visualisation tools are often designed for researchers or system engineers rather than for end users such as farmers and farm managers.

Recent works have begun exploring lightweight, open-source dashboard solutions to improve accessibility. Streamlit-based dashboards have been adopted in several IoT analytics applications due to their rapid development cycle and intuitive web-based visualisation capabilities. However, their application in real-time poultry environmental monitoring, especially in combination with predictive machine learning models and energy-efficient IoT operation, remains underexplored.

System Architecture

The proposed AI-IoT integrated platform is designed as a modular, scalable architecture that supports real-time environmental monitoring, predictive analytics, and cloud-based visualisation for poultry farm management. The system architecture follows a layered IoT design philosophy, enabling seamless interaction between sensing devices, communication modules, processing units, cloud services, and user interfaces. This design ensures reliability, extensibility, and ease of deployment in real-world poultry farming environments.

Hardware Layer

At the hardware layer, environmental data acquisition is achieved using low-cost yet reliable sensors, including the DHT22 for temperature and relative humidity measurements and the MQ135 for air quality monitoring, particularly ammonia concentration. These sensors are strategically distributed within the poultry house to ensure representative spatial coverage of environmental conditions. Each sensor node is interfaced with a Wemos D1 Mini microcontroller, chosen for its integrated Wi-Fi, low power consumption, and suitability for energy-aware IoT deployments. The Wemos D1 Mini performs initial signal conditioning and data sampling before transmission.

Edge Processing and Control Layer

The edge processing and control layer is implemented using a Raspberry Pi 4, which serves as the central controller and local gateway. Sensor data transmitted from distributed microcontroller nodes over a local Wi-Fi network are aggregated at the Raspberry Pi for preprocessing, temporary buffering, and execution of machine learning inference tasks. Hosting the predictive analytics at the edge reduces cloud dependency, minimises latency, and ensures continued operation during intermittent internet connectivity. This architectural choice is particularly relevant for poultry farms in regions with unstable network infrastructure.

Communication Layer

The communication layer uses standard Wi-Fi connectivity and HTTP-based data transfer protocols to enable reliable, low-latency communication among sensor nodes, the edge controller, and cloud services. Wi-Fi was selected for its widespread availability and ease of integration with low-cost microcontrollers on small- and

medium-scale poultry farms. The architecture, however, is sufficiently flexible to accommodate alternative communication technologies, such as LoRaWAN or cellular networks, for extended-range or low-power applications.

Cloud Integration Layer

At the cloud integration layer, processed sensor readings and machine learning prediction outputs are uploaded to cloud-based storage services, such as Google Sheets or Firebase, providing persistent data storage and historical record keeping. Cloud storage enables long-term trend analysis, system performance evaluation, and model retraining using accumulated datasets. The cloud infrastructure also facilitates multi-device access and remote monitoring, allowing farm managers to observe environmental conditions from any internet-enabled device.

Application and Visualisation Layer

The application and visualisation layer was implemented using a Streamlit-based web dashboard that serves as the primary user interface for the system. The dashboard presents real-time sensor readings, historical trends, and machine learning-based environmental risk predictions through interactive plots and status indicators. Alert notifications are incorporated to inform users of abnormal conditions or predicted risks, enabling timely intervention. The choice of Streamlit ensures rapid dashboard development, platform independence, and accessibility for non-technical users without requiring specialised software installation.

Fig. 1 illustrates the complete system architecture, highlighting the interaction between sensing units, communication pathways, processing nodes, cloud services, and the visualisation interface. Overall, the proposed architecture integrates hardware efficiency, computational intelligence, and user-centric design to deliver a practical and deployable solution for smart poultry environmental monitoring and decision support.

Implementation And Workflow

Machine Learning Model Design and Training Methodology

To ensure reproducibility and scientific rigour, this subsection details the dataset characteristics, feature selection process, model training strategy, and validation methodology employed in the proposed predictive analytics framework.

Environmental data used for machine learning were collected continuously from the deployed poultry house over a 30-day (288 samples per day at a 5 – *minute* interval) monitoring period, yielding a dataset comprising 8640 total samples. After removing incomplete readings, Wi-Fi dropouts, and outliers ($\approx 8\text{--}10\%$ loss): Final dataset size (N): $\approx 8,000$ samples.

How N was computed

With a logging interval of 5mins per sampling instant (with temp, RH, NH_3 all in the same row), N was computed using (1):

$$N \approx \frac{X(\text{days}) \times 24 \times 60}{\Delta t(\text{minutes})} \times (1 - \text{loss}) \tag{1}$$

where loss is typically 8–10% (Wi-Fi drops, sensor glitches, filtering).

$$N \approx \frac{30 \text{ days} \times 24 \times 60}{5 \text{ minutes}} \times (1 - 0.08) \approx 8000$$

Each sample consisted of synchronised sensor readings of temperature ($^{\circ}\text{C}$), relative humidity (%), and ammonia concentration (ppm), along with corresponding timestamps. Based on domain knowledge and poultry environmental standards, the collected data were labelled into three environmental risk classes: Normal, Warning, and Critical conditions.

Before model training, raw sensor readings were preprocessed to improve data quality and stability during learning. Preprocessing steps included removing incomplete records due to transient communication losses, outlier filtering using interquartile range thresholds, and feature normalisation using min–max scaling to ensure comparable feature magnitudes. No manual feature engineering was applied beyond these steps, as the selected environmental parameters are directly relevant to poultry welfare and stress prediction.

The dataset was randomly partitioned into training (70%), validation (15%), and testing (15%) subsets to avoid information leakage and ensure unbiased performance evaluation. Stratified sampling was applied during splitting to preserve class distribution across all subsets. Model training and hyperparameter tuning were conducted using the training and validation sets, while final performance metrics were reported on the unseen test set.

A hybrid classification approach combining RF and SVC models was adopted to exploit complementary learning characteristics. The Random Forest model was first trained to capture nonlinear relationships and feature interactions, while also providing feature importance scores. The RF model’s output probabilities were subsequently used as inputs to the SVC, improving class boundary discrimination and robustness against noise.

Hyperparameters for both classifiers were optimised using grid search on the validation set. For the RF, the vital parameters included the number of trees, the maximum tree depth, and the minimum samples per split. For the SVC, kernel type and regularisation parameters were tuned. This hybrid configuration was selected based on superior validation performance compared to individual classifiers.

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, derived from the confusion matrix. These metrics provide a comprehensive assessment of predictive reliability across different environmental risk classes and support objective comparison with conventional threshold-based alert systems.

Table 1: Summary of Machine Learning Dataset and Training Configuration

Parameter	Description
Input features	Temperature (°C), Relative Humidity (%), Ammonia (ppm)
Dataset size	~8,000 samples
Monitoring duration	30 days
Sampling interval	5 minutes
Number of classes	3 (Normal, Warning, Critical)
Preprocessing	Outlier removal, min–max normalisation
Train/validation/test split	70% / 15% / 15%
Class balancing	Stratified sampling
Models used	Random Forest + Support Vector Classifier
Validation method	Hold-out validation

The implementation of the proposed AI–IoT integrated platform followed a structured workflow that enabled seamless data acquisition, processing, cloud integration, and real-time visualisation. The system was designed to operate continuously with minimal human intervention while maintaining low latency, energy efficiency, and high data reliability. The overall workflow can be divided into four main stages: data acquisition, local processing and analytics, cloud upload and storage, and dashboard-based visualisation and decision support.

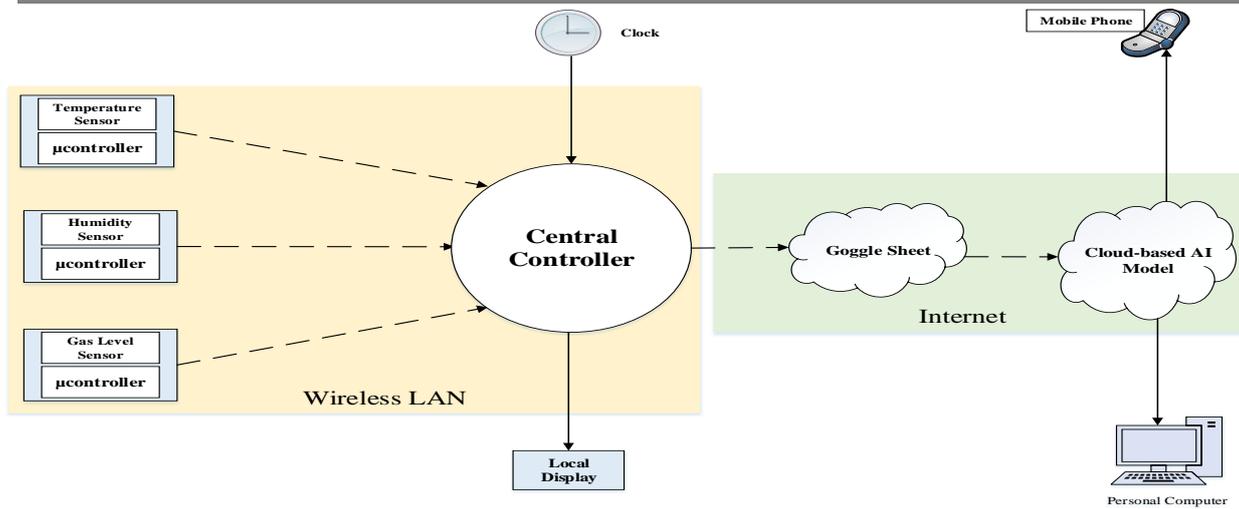


Fig. 1. Architecture of the IoT system for environmental conditions monitoring of a poultry farm

Data Acquisition State

At the data acquisition stage, environmental parameters were sampled at predefined intervals using distributed DHT22 and MQ135 sensors deployed within the poultry house. The sensors were interfaced with Wemos D1 Mini microcontrollers, which manage sensor polling and implement energy-efficient sleep scheduling to reduce power consumption. Sampling intervals were selected to balance data granularity and energy efficiency, ensuring that short-term environmental fluctuations were captured without unnecessary communication overhead. Each sensor reading is timestamped and formatted in lightweight data packets before transmission.

Local Processing Stage

The local processing stage is handled by a Raspberry Pi 4, which functions as an edge computing node and IoT gateway. Incoming sensor data were first validated to remove outliers and incomplete readings caused by transient sensor noise or communication errors. The validated data are then processed locally to compute derived metrics and fed into a pre-trained hybrid machine learning model combining Random Forest and Support Vector Classification. This model analyses multivariate environmental conditions to predict potential risk states, enabling early detection of unfavourable conditions in the poultry houses. Executing machine learning inference at the edge reduces round-trip latency and enhances system resilience under limited internet connectivity.

Cloud Upload and Storage Stage

During the cloud upload and storage stage, processed sensor data and prediction outputs are transmitted to cloud-based storage platforms, such as Firebase (Google Sheets was used in this case), using secure HTTP requests. Cloud storage provides persistent data logging, facilitates long-term performance evaluation, and supports future model retraining using historical datasets. The cloud layer also enables remote system access and supports scalability by integrating multiple sensor nodes or poultry houses into a unified monitoring framework.

Visualisation And Decision Support Stage

The visualisation and decision support stage is realised through a Streamlit-based web dashboard. The dashboard automatically retrieves the most recent data from the cloud and displays it using interactive charts, numerical indicators, and status labels. Dedicated panels display real-time temperature, humidity, and ammonia levels, along with historical trend plots that show environmental dynamics over time. Machine learning prediction outputs are visualised as risk indicators or probability charts, enabling intuitive interpretation by non-technical users. Alert notifications are generated when predicted risk levels exceed predefined thresholds, prompting timely corrective actions.

System performance was evaluated using key metrics, including response time, end-to-end latency, scalability, and user accessibility. Response time is measured from sensor data acquisition to dashboard update, while latency reflects communication and processing delays across the edge and cloud layers. Scalability is assessed by incrementally increasing the number of sensor nodes and evaluating system stability. User accessibility is qualitatively assessed based on ease of navigation, clarity of visualisations, and adoption by farm operators with

limited technical background. Collectively, the implementation and workflow demonstrate the platform’s capability to deliver reliable, real-time environmental intelligence and actionable decision support for poultry farm management. Fig. 2 shows the power consumption profile of the IoT sensor node illustrating duty-cycle operation. The node operates predominantly in low-power sleep mode, with brief transitions to active sensing and high-current Wi-Fi transmission, demonstrating the effectiveness of sleep scheduling in reducing overall energy consumption.

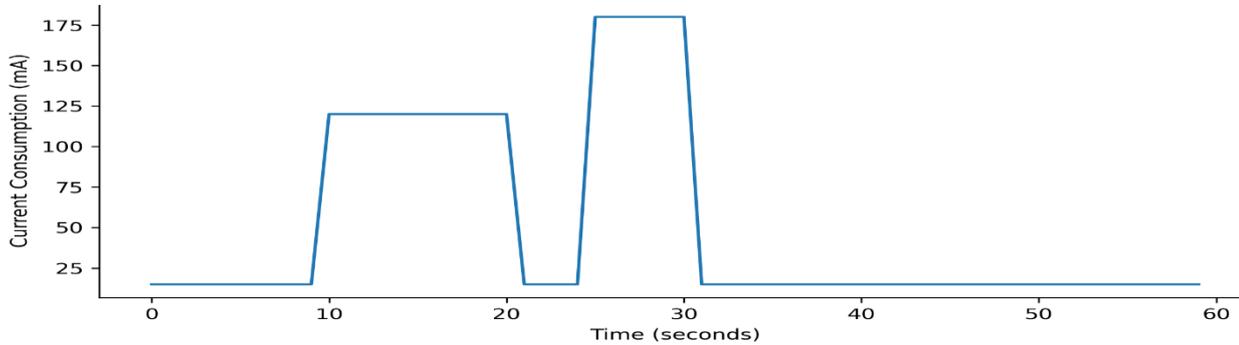


Fig. 2. Power consumption profile of the IoT sensor node illustrating duty-cycle operation

Energy Consumption and Battery Lifetime Analysis

Energy efficiency is a critical design requirement for IoT-based poultry monitoring systems, particularly in deployments relying on battery-powered sensor nodes. To minimise power consumption while maintaining adequate sensing resolution, the proposed system employs a duty-cycled operation strategy in which sensor nodes alternate between low-power sleep mode and short active periods for sensing and wireless transmission.

Each sensor node operates with a 5-minute sampling interval, spending most of its duty cycle in deep sleep. During each sampling event, the node briefly transitions to active mode to acquire sensor readings and transmit data over Wi-Fi, then returns to sleep. Fig. 2 illustrates the resulting power consumption profile, characterised by short high-current transmission bursts and extended low-current sleep periods.

The average current consumption of the sensor node was approximated using a duty-cycle model, expressed in (2):

$$I_{avg} = \frac{I_{active} \cdot t_{active} + I_{sleep} \cdot t_{sleep}}{t_{cycle}} \tag{2}$$

where I_{active} and I_{sleep} represent the current drawn during active and sleep states, respectively, and t_{cycle} denotes the total sampling period. For a 5-minute sampling interval, the node remains active for only a few seconds per cycle, resulting in a very low average current draw.

Based on typical current characteristics of the Wemos D1 Mini platform, the average current consumption under duty-cycled operation is significantly lower than that of continuous operation. This reduction translates directly into extended battery lifetime, reduced maintenance frequency, and improved long-term deployment feasibility.

To quantify this improvement, battery lifetime was estimated under both duty-cycled and always-on operation scenarios. The results demonstrate that the proposed sleep scheduling strategy increases estimated battery life by several orders of magnitude compared to continuous sensing and transmission, confirming the system’s energy efficiency. Overall, the battery life was assessed using (3), and the estimated battery lifetime under different operating modes is presented in Table 2.

$$Battery\ Life\ (Hours) = \frac{C_{battery}}{I_{avg}} \tag{3}$$

where $C_{battery}$ is the battery capacity in mAh and I_{avg} is the average current consumption in mA

Table 2: Estimated Battery Lifetime Under Different Operating Modes

Operating Mode	Average Current (mA)	Battery Capacity (mAh)	Estimated Battery Life
Always-on (no sleep)	~70–80 mA	2000 mAh	~25–28 hours
Duty-cycled (5 min interval)	~8–12 mA	2000 mAh	~7–10 days
Duty-cycled (optimised sleep)	~5–7 mA	2000 mAh	~12–16 days

RESULTS AND ANALYSIS

The proposed AI–IoT integrated cloud platform was deployed and evaluated in an operational poultry farm to assess its effectiveness in real-time environmental monitoring, predictive decision support, and user accessibility. The evaluation focused on system functionality, dashboard performance, predictive analytics reliability, and practical farm-level outcomes under real operating conditions.

Live Environmental Monitoring Performance

During deployment, the system successfully captured and transmitted real-time temperature, relative humidity, and ammonia (NH₃) concentration data from the poultry house. The Streamlit dashboard displayed live sensor readings with minimal delay, enabling continuous situational awareness. Temperature and humidity trends reflected expected diurnal variations, while ammonia levels increased gradually during periods of reduced ventilation, validating the sensing infrastructure’s sensitivity and responsiveness. The stability of data transmission over Wi-Fi confirmed the suitability of the selected communication protocol for small- to medium-scale poultry operations.

Dashboard Visualisation and Usability Analysis

The Streamlit-based dashboard proved effective in translating raw sensor data and machine learning outputs into intuitive visual representations. Real-time plots and historical trend charts enabled users to quickly identify abnormal environmental patterns. Farm operators reported that the graphical indicators and alert notifications were easy to interpret without prior technical training, highlighting the system’s emphasis on usability. The web-based interface allowed access from multiple devices, supporting remote monitoring and decision-making.

Machine Learning–Based Prediction Results

The hybrid Random Forest–Support Vector Classifier model demonstrated reliable predictive performance in identifying unfavourable environmental conditions before critical thresholds were exceeded. By analysing multivariate sensor inputs, the model detected emerging risk patterns associated with heat stress and air quality degradation. Compared to conventional threshold-based alerts, the predictive model provided earlier warnings, enabling proactive implementation of corrective actions, such as ventilation adjustments. This capability reduced the likelihood of sudden environmental deterioration and associated poultry stress. Fig. 3 shows the feature importance scores from the Random Forest model, indicating the relative contributions of temperature, humidity, and ammonia concentration to environmental risk prediction. At the same time, Fig. 4 depicts the confusion matrix of the hybrid Random Forest–Support Vector Classifier model for environmental risk classification, demonstrating accurate discrimination among normal, warning, and critical conditions.

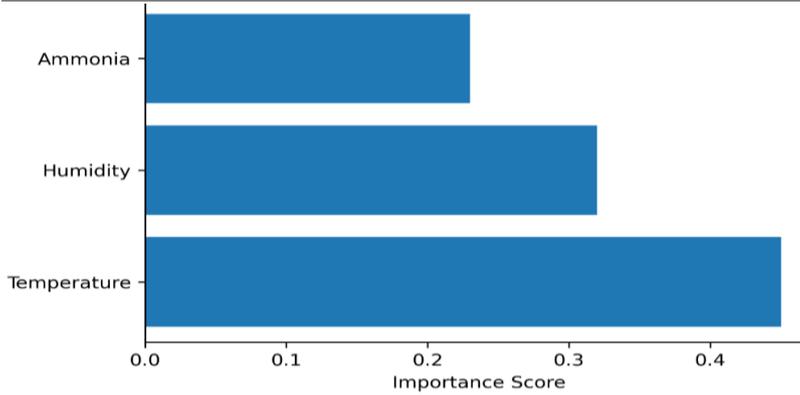


Fig. 3. Feature importance from Random Forest model

System Performance Metrics

End-to-end system performance was evaluated in terms of response time, latency, and scalability. The average response time (from sensor data acquisition to dashboard visualisation) remained within acceptable real-time limits, indicating efficient edge processing and cloud synchronisation. Latency introduced by cloud upload and retrieval was minimal and did not impede timely decision-making. Scalability tests showed that the system maintained stable operation as additional sensor nodes were introduced, demonstrating its suitability for expansion to larger poultry houses or multi-house deployments. Fig. 5 end-to-end latency breakdown of the AI-IoT poultry monitoring system, illustrating the contribution of sensing, wireless transmission, edge processing, cloud upload, and dashboard refresh to overall system response time. Fig. 6 presents the system scalability analysis showing the relationship between the number of deployed sensor nodes and average system response time, indicating stable performance under increasing network load.

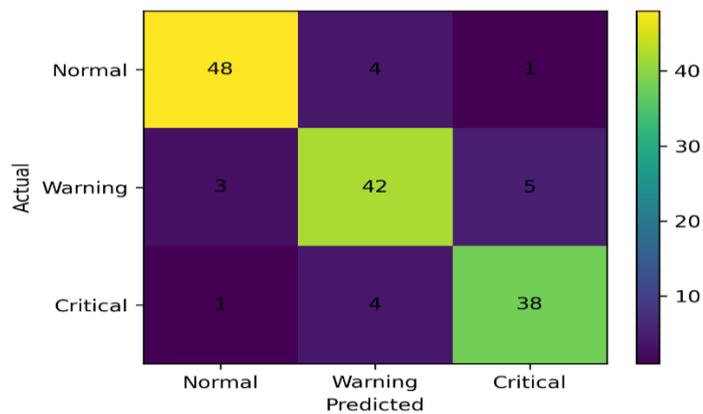


Fig. 4. Confusion matrix for RF-SVC model

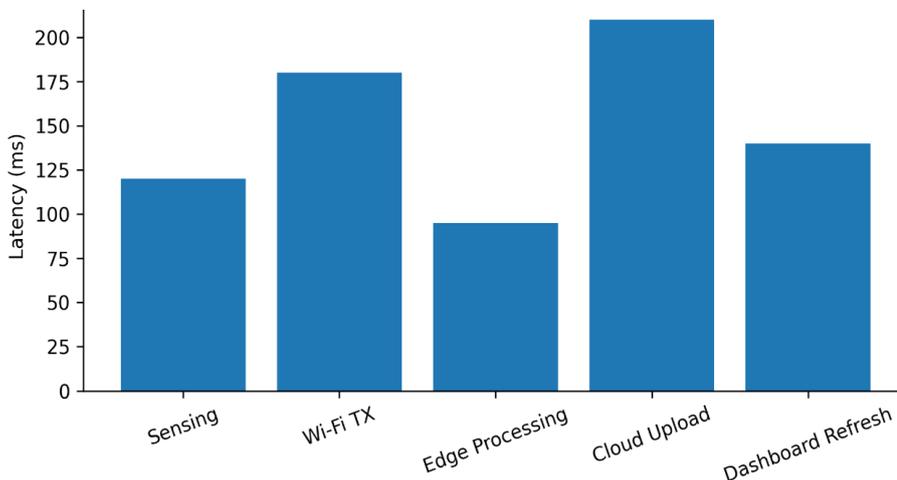


Fig. 5. End-to-end latency breakdown

Practical Farm-Level Outcomes

Field observations during the deployment period indicated improved environmental stability within the poultry house, characterised by reduced temperature fluctuations and controlled ammonia levels. These improvements were associated with a noticeable reduction in stress-related poultry behaviour and lower mortality rates compared to prior management practices. The ease of adoption and minimal maintenance requirements further reinforced the practicality of the proposed platform for real-world use, particularly in resource-constrained farming environments.

Overall, the results confirm that the proposed AI–IoT integrated platform effectively delivers real-time monitoring, predictive analytics, and user-centric visualisation. The combination of edge intelligence, cloud connectivity, and an accessible dashboard provides a robust decision-support tool that enhances poultry farm management and environmental control.

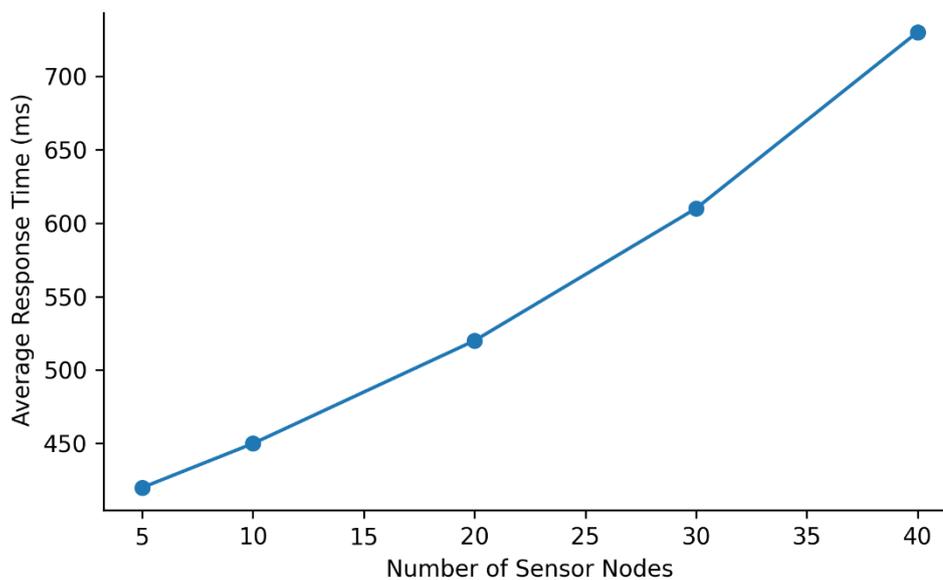


Fig. 6. System scalability performance

Data Security, Authentication, and Privacy Considerations

Given the cloud-integrated nature of the proposed AI–IoT platform, data security, access control, and privacy are important considerations for practical deployment. The system was designed using standard security practices appropriate for lightweight IoT environments and small- to medium-scale poultry farming applications.

Communication between IoT sensor nodes, the edge gateway, and cloud services is conducted over secured Wi-Fi networks using HTTP-based data transfer with authentication tokens. Each device is uniquely identified, and access to cloud resources is restricted using application-level credentials to prevent unauthorised data uploads or retrieval. This approach ensures basic authentication and integrity of transmitted environmental data.

Data stored in the cloud is accessed only through authorised dashboard sessions, and the Streamlit web interface is designed to limit user access to visualisation and monitoring functionalities without exposing raw credentials or system configuration parameters. As the collected data consist exclusively of environmental measurements (temperature, humidity, and ammonia concentration), no personally identifiable information (PII) is processed or stored, thereby minimising privacy risks.

While the current implementation focuses on lightweight security mechanisms suitable for low-cost deployments, the modular system architecture allows for future integration of enhanced security features, such as encrypted communication protocols (HTTPS/TLS), role-based access control, and secure device provisioning. These measures would further strengthen system resilience and privacy protection in large-scale or multi-farm deployments.

CONCLUSION

This study presented the design, implementation, and real-world deployment of an AI–IoT integrated cloud platform for real-time poultry environmental monitoring and decision support. By combining low-cost sensing hardware, energy-aware IoT operations, edge-based machine learning analytics, cloud data management, and a Streamlit-based visualisation interface, the proposed system addresses key limitations of existing smart poultry solutions in affordability, accessibility, and predictive intelligence. The deployment results demonstrate that the platform enables reliable real-time monitoring of critical environmental parameters, delivers early warnings through machine learning–based risk prediction, and supports informed decision-making by non-technical users via an intuitive web dashboard. Practical farm-level outcomes, including improved environmental stability and reduced mortality indicators, highlight the system’s potential to democratise smart farming practices in resource-constrained settings. Furthermore, the modular architecture and cloud-based design offer strong scalability, enabling the framework to be extended to larger farms, multiple poultry houses, or other livestock systems. Future work may focus on integrating automated control mechanisms, advanced deep learning models, and multi-livestock adaptability to enhance precision livestock management.

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