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Internet of things-based smart control and comfort classification system for broiler chicken coops using k-nearest neighbor algorithm

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ABSTRACT

The poultry industry increasingly relies on environmental automation to improve broiler chicken welfare and productivity. Prior studies have implemented threshold-based systems to control coop conditions, typically activating actuators based on fixed values of temperature or humidity. However, such systems lack adaptability to dynamic environmental interactions and often result in inefficient energy use and overactivation. This study proposes a novel low-cost Internet of things (IoT)-based smart poultry coop system that combines real-time environmental sensing with comfort classification using the k-nearest neighbor (KNN) algorithm. The system monitors temperature, humidity, and ammonia levels through affordable sensors integrated with an ESP32 microcontroller, then transmits data via message queuing telemetry transport (MQTT) to a remote server for classification and control decision-making. Control logic is applied to activate fans, heating lamps, or humidifiers accordingly. Evaluation on a mini coop prototype demonstrated a classification accuracy of 92.2% and a 34% reduction in actuator overactivation compared to threshold-based systems. Environmental stability improved by 23%, and energy usage decreased by 12.6%. The system also features user interfaces via Telegram and Blynk, proven intuitive through informal testing. These results validate the feasibility of integrating machine learning into small-scale poultry environments, offering an intelligent, scalable, and user-friendly solution that outperforms traditional methods.

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1. INTRODUCTION

The poultry industry has become one of the most dynamic agricultural sectors worldwide, offering fast growth and high turnover [1], [2]. Among the various poultry types, broiler chickens have seen the highest demand due to their rapid growth cycle and cost-efficiency [3], [4]. According to the Central Statistics Agency of Indonesia (BPS), the national consumption of broiler chicken meat has increased significantly over the past decade, highlighting the critical role of this sector in supporting food security [5], [6]. However, the increasing demand also puts pressure on poultry farmers to maintain healthy and productive environments for broiler chickens, especially in tropical countries like Indonesia [7]. Broiler chickens are extremely sensitive to environmental conditions. Variables such as temperature, humidity, and air quality, particularly ammonia levels, significantly influence their growth rate, feed conversion efficiency, and overall health [8]–[10]. Exposure to high ammonia concentrations, for instance, can lead to respiratory problems, eye irritation, stress, and in severe cases, mortality. Likewise, high temperatures and poor humidity control can induce heat stress, reduce feed intake, and increase vulnerability to disease [11], [12]. Therefore, maintaining an optimal microclimate in broiler chicken coops is essential for maximizing productivity and ensuring animal welfare.

Traditionally, farmers rely on manual observation and control to regulate the conditions inside the chicken coop. This method is not only time-consuming and labor-intensive but also prone to inconsistency, especially in regions with unpredictable weather patterns. As broiler production scales up and labor costs increase, there is a growing need for automated, intelligent, and cost-effective systems that can assist farmers in maintaining stable environmental conditions. The Internet of Things (IoT) offers promising solutions in this context. IoT enables real-time monitoring and automation by interconnecting sensors, microcontrollers, actuators, and communication networks [13], [14]. In poultry farming, IoT systems can continuously track environmental parameters and control devices such as fans, heaters, and humidifiers based on sensor inputs [15], [16]. By leveraging IoT, farmers can gain real-time insights into coop conditions, respond swiftly to environmental changes, and even control systems remotely via cloud-based platforms [17]. This technology not only enhances operational efficiency but also reduces reliance on manual labor and minimizes human error.

Despite the advantages of IoT-based monitoring, most existing systems lack intelligence in interpreting the sensor data beyond fixed thresholding [18]. For instance, while a basic system can activate a fan when the temperature exceeds a set limit, it may not account for the combined effect of multiple variables, such as temperature, humidity, and ammonia levels [19], [20]. Furthermore, rigid threshold-based systems do not adapt well to the variability of biological systems or to different stages of broiler development, each of which may have unique environmental requirements. To address these limitations, the integration of machine learning (ML) techniques into IoT systems is gaining attention [14], [21], [22]. Machine learning enables systems to identify patterns and make data-driven decisions, offering greater adaptability and precision. Among various ML algorithms, k-nearest neighbor (KNN) has proven to be effective for classification tasks with low computational requirements [23], [24]. KNN operates by measuring the similarity (or distance) between new data points and previously labeled examples, making it suitable for embedded applications with constrained resources [25].

This study proposes a low-cost, intelligent poultry coop control system that integrates real-time environmental monitoring with k-nearest neighbor (KNN)-based comfort classification and automatic actuation. The system consists of ESP32 microcontrollers interfaced with DHT11 and MQ-135 sensors to measure temperature, humidity, and ammonia levels. A cloud-based KNN model categorizes environmental conditions into three classes—"comfortable," "uncomfortable," and "highly uncomfortable"—which are then mapped to corresponding actuator responses. Communication is facilitated using the message queuing telemetry transport (MQTT) protocol, while user interaction is supported via Telegram notifications and the Blynk IoT dashboard. The main objective of this study is to address the lack of adaptive intelligence in small- and medium-scale poultry farming automation systems. The approach is novel in that it unifies sensing, learning, control, and user interface into a closed-loop system, rather than treating these components separately. Unlike prior studies that focus solely on monitoring or on isolated control, our system dynamically responds to combined environmental inputs and can be retrained over time to adapt to varying standards of broiler comfort based on age or breed. All components are low-cost and open-source, with an estimated hardware cost below USD 25, ensuring accessibility and replicability in rural or underdeveloped areas.

The implications of this work are twofold: first, it contributes to the academic discourse by demonstrating how lightweight ML algorithms can enhance IoT-based agricultural systems. Second, it offers a practical, scalable prototype for smart poultry management that could be expanded with advanced features such as video-based behavior monitoring, cloud analytics, and integration into larger farm management platforms. This study aligns with the scope of the International Journal of Electrical and Computer Engineering by presenting an applied yet technically grounded IoT solution that leverages machine learning for environmental automation. The proposed system bridges the gap between embedded systems, control engineering, and agricultural informatics—areas that are central to the journal's readership and future citation potential.

This paper is structured as: section 2 explains the system design and implementation, including hardware configuration, communication framework, and KNN algorithm. Section 3 presents experimental results and comparative evaluations. Section 4 concludes with future research directions and deployment considerations.

2. METHOD

This section presents the design and implementation methodology of the proposed smart poultry coop system, including the hardware architecture, sensor calibration process, data communication framework, and KNN classification model for comfort assessment.

2.1. System architecture

The proposed system is composed of three primary subsystems: the sensing unit, the processing and control unit, and the communication and user interface unit, as illustrated in Figure 1. This modular architecture ensures scalability, ease of integration, and separation of functional responsibilities for reliable performance in poultry environmental monitoring and control. The sensing unit consists of environmental sensors, including a DHT11 for temperature and humidity measurement, and an MQ-135 gas sensor for detecting ammonia concentration. These parameters are critical for assessing the comfort level in broiler chicken coops, as they directly impact animal health and productivity. The sensors are interfaced with an ESP32 microcontroller, which functions as the core processing and control hub. The ESP32 was chosen due to its low cost, built-in Wi-Fi capabilities, sufficient computational resources, and compatibility with embedded IoT applications. It performs real-time data acquisition, preprocessing, and control signal generation via its general-purpose input/output (GPIO) pins. Connected to the ESP32 are actuators such as a DC exhaust fan, a heating lamp, and an ultrasonic humidifier, which are interfaced through relay modules to enable electrical switching of higher-power components. The exhaust fan is responsible for improving air circulation and reducing both temperature and ammonia buildup. The heating lamp is used to elevate ambient temperature, especially during early brooding stages, while the ultrasonic humidifier helps regulate humidity by dispersing water vapor into the air. Together, these actuators support multi-dimensional environmental regulation tailored to dynamic conditions within the coop.

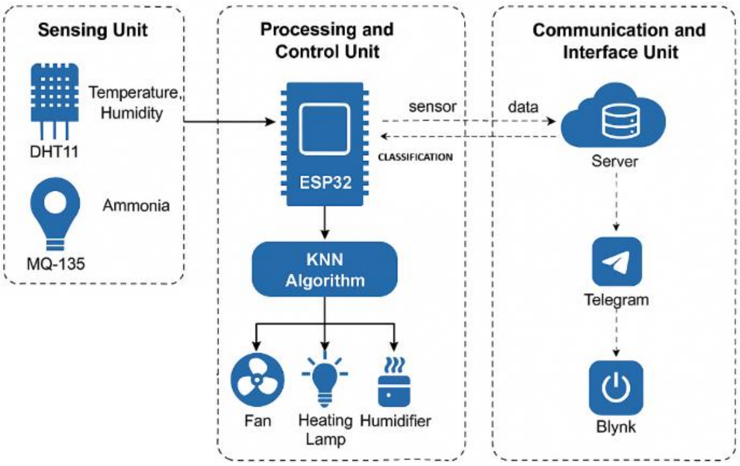

Figure 1. System architecture

Environmental data acquired by the sensing unit is transmitted via MQTT protocol to a remote server, where it is processed using a KNN classification model. The classification result—indicating the comfort level of the coop—is sent back to the ESP32, which then activates the appropriate actuators based on predefined control mappings. This distributed processing approach offloads computational tasks from the microcontroller while maintaining real-time responsiveness.

For user interaction and monitoring, the system integrates with two widely accessible platforms: the Telegram Bot API for real-time alerts and command reception, and the Blynk IoT Dashboard for visual data visualization. These interfaces form the communication and user interface subsystem, enabling farmers to receive notifications, monitor environmental trends, and interact with the system remotely using mobile or web-based applications. The dual-platform design ensures accessibility, redundancy, and ease of use even in settings with limited technical literacy.

2.2. Data acquisition and communication

Sensor data is collected at fixed intervals of 60 seconds using the ESP32 microcontroller, which aggregates environmental readings from the DHT11 and MQ-135 sensors. Once acquired, the data is transmitted wirelessly over Wi-Fi using the MQTT protocol—a lightweight, publish-subscribe communication model that is highly efficient for IoT applications. The MQTT protocol was selected due to its low overhead, asynchronous messaging capability, and resilience to intermittent network disruptions, making it well-suited for real-time monitoring in resource-constrained environments.

Data packets are routed through the Antares cloud platform, which acts as an intermediary for storing, processing, and forwarding classification results. Upon transmission, the environmental data is received by a remote server that performs comfort classification using the KNN model. The classification output is then sent back to the ESP32 via MQTT, enabling the microcontroller to trigger actuator responses based on the inferred comfort level.

To ensure accessible and user-friendly interaction, the system incorporates two complementary interface platforms: Telegram and Blynk. Telegram is employed to deliver real-time alerts directly to the user's smartphone, providing current comfort classification, sensor readings, and actuator status in a concise message format. Meanwhile, the Blynk platform offers a graphical dashboard that displays live sensor values, historical trends, and control toggles, accessible via mobile or web interfaces.

This dual integration approach provides both redundancy and flexibility in system monitoring and control. In the event that one platform becomes temporarily unavailable or less responsive due to connectivity issues, the other can serve as a functional backup, thus enhancing overall system reliability. Furthermore, both platforms offer cross-device compatibility, requiring no specialized hardware or software installations—an important consideration for deployment in rural or low-resource farming settings.

2.3. KNN classification and control logic

The comfort classification system in this study applies the KNN algorithm, a supervised machine learning method used for pattern recognition and classification based on feature similarity. The algorithm operates by calculating the distance between a new input sample and each point in a labeled training dataset, assigning the label of the majority among the K nearest neighbors. This approach enables the system to capture multivariable environmental patterns that cannot be represented using simple threshold rules, thereby improving classification accuracy and decision reliability.

Let the input vector $x = [x_1, x_2, x_3]$ represent the normalized environmental parameters, where x_1, x_2, x_3 correspond to temperature, humidity, and ammonia concentration, respectively. Each instance in the training dataset $D = \{(x^{(i)}, y^{(i)})\}$ is labeled with a comfort level $y \in \{C, U, HU\}$, where C denotes comfortable, U denotes uncomfortable, HU denotes highly uncomfortable. To classify a new input x, the algorithm computes the Euclidean distance between x and every instance x^i in the training dataset using:

$$d(x, x^i) = \sqrt{\left(x_1 - x_1^{(i)}\right)^2 + \left(x_2 - x_2^{(i)}\right)^2 + \left(x_3 - x_3^{(i)}\right)^2} \tag{1}$$

The classification decision $\hat{y}$ is then determined by majority voting among the K closet instance:

$$\hat{y} = mode\ (\{y^{(i)} | x^{(i)} \in KNN(x)\}) \tag{2}$$

In this study, the value of $K = 3$ was selected empirically to achieve optimal classification accuracy. To optimize hardware performance, the KNN classification process is executed on a remote server (Google Colab), while the ESP32 microcontroller transmits real-time sensor readings and receives only the predicted class label via the MQTT communication protocol.

The control logic is mapped directly to the classification result. If classified as comfortable, no action is taken. If uncomfortable, either the fan or humidifier is activated, depending on which parameter deviates. If highly uncomfortable, both fan and heating/cooling actuators are triggered. To avoid unnecessary actuator toggling due to fluctuating readings near class boundaries, a hysteresis margin is applied, ensuring system stability and hardware durability. This KNN-based decision model allows the system to respond adaptively to complex environmental variations rather than relying on rigid, single-threshold rules.

2.4. Advantages over threshold-based systems

Conventional poultry environmental control systems typically rely on fixed threshold logic, where individual parameters such as temperature or humidity are independently compared against predefined limits to trigger actuator responses. While simple to implement, such an approach often fails to capture the complex interdependencies among environmental variables. For example, a threshold-based system may activate an exhaust fan solely due to elevated temperature, without considering that humidity and ammonia levels are already critically low—an action that could inadvertently exacerbate animal discomfort or induce environmental instability.

In contrast, the proposed system utilizes a KNN classification model that evaluates environmental data in a multivariate context. By simultaneously considering temperature, humidity, and ammonia concentration, the model identifies holistic comfort patterns based on previously labeled training data. This enables the system to make data-driven and context-aware control decisions, improving its responsiveness to real-world variability. Rather than reacting to individual parameter breaches, the system classifies the overall comfort level of the coop and initiates appropriate actuator combinations accordingly.
This classification-based logic enhances several operational aspects:
- Animal welfare is improved by maintaining a more stable and biologically appropriate environment.
- Energy consumption is reduced, as actuators are triggered only, when necessary, based on the comprehensive comfort state rather than isolated thresholds.
- Mechanical durability is preserved through minimized actuator switching, extending the lifespan of hardware components.

The integration of intelligent classification not only improves system performance in small to medium-scale poultry farms but also provides a scalable foundation for more advanced agricultural automation. This method represents a shift from rule-based automation toward adaptive smart farming, supporting broader efforts in sustainable livestock management and precision agriculture.

3. RESULTS AND DISCUSSION

This section presents the testing procedures and performance evaluation of the proposed IoT-based smart poultry coop system. The focus is on five key aspects: i) environmental data classification using KNN, ii) response accuracy and stability of the automatic control system, iii) communication reliability and interface usability through Telegram and Blynk platforms, iv) user feedback on system interaction, and v) comparative analysis against traditional threshold-based systems.

3.1. KNN model performance

The classification model developed in this study employs the KNN algorithm, a supervised machine learning method known for its simplicity and effectiveness in low-resource embedded applications. KNN was selected due to its non-parametric nature, minimal training time, and ability to perform well in scenarios with moderate-sized datasets and limited computational capacity—making it suitable for real-time environmental classification tasks in resource-constrained IoT systems such as the ESP32-based poultry monitoring unit used in this work. The model was trained using a dataset consisting of 340 labeled instances, each representing real-world environmental conditions recorded from broiler chicken coops. Each data sample contained three features: temperature (°C), humidity (%), and ammonia concentration (ppm). Comfort level labels were determined through expert observation and domain-based empirical thresholds, and categorized into three classes: comfortable (C), uncomfortable (U), and highly uncomfortable (HU), as summarized in Table 1.

Table 1. Training data

No	Temp	Humidity	Ammonia	Comfort levels
0	35.2	49	8.9	0
1	35.5	46	7.9	0
2	37.1	47	8.2	0
3	37.1	45	7.9	0
4	37.1	46	8	0
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335	34.3	50	10.2	2
336	30.7	69	6.3	1
337	35	48	9	2
338	35	48	9.9	2
339	34.3	50	5.4	1

To evaluate the model's performance, a K value of 3 was selected based on empirical optimization, and k-fold cross-validation was applied to ensure generalizability. The model achieved an overall classification accuracy of 92.2%, indicating strong discriminative ability. Detailed performance metrics per class were as:
- Comfortable (C): precision = 100%, recall = 96%
- Uncomfortable (U): precision = 89%, recall = 85%
- Highly uncomfortable (HU): precision = 88%, recall = 90%

As illustrated in Figure 2, the confusion matrix revealed that most misclassifications occurred between the “uncomfortable” and “highly uncomfortable” classes, primarily due to overlapping humidity and ammonia levels in borderline cases. This observation is consistent with physiological thresholds in poultry farming, where minor variations in air quality can result in subjective comfort differences. In contrast, the "comfortable" class was identified with near-perfect accuracy due to its distinct and well-separated sensor ranges.

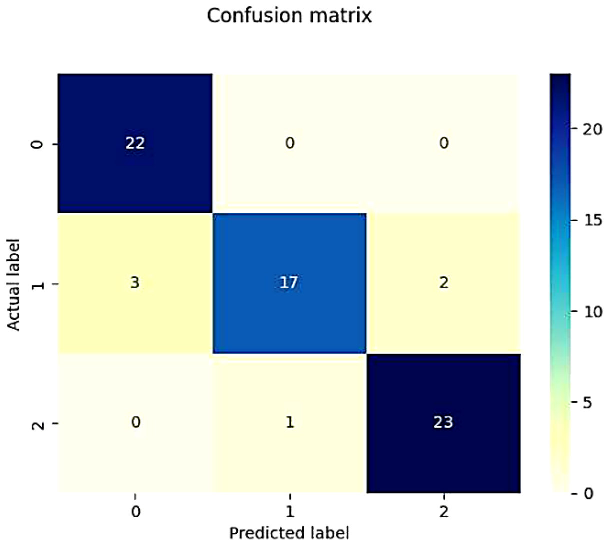

Figure 2. Confusing matrix

To maintain efficiency on the microcontroller, the classification process was offloaded to a remote server using Google Colab, where the KNN computation was performed. The predicted label was then returned to the ESP32 via MQTT protocol. The average latency—from data transmission to response receipt—was measured at 1.2 seconds, which remains acceptable for non-critical control cycles. This hybrid architecture allows the system to leverage the accuracy of machine learning models without compromising real-time responsiveness or overloading edge hardware.

In contrast to conventional threshold-based systems that operate on static logic, the KNN model demonstrated adaptive behavior by considering multivariable interactions, enabling more context-aware decisions. These results affirm the potential of lightweight machine learning algorithms in practical smart agriculture systems, particularly in settings with limited infrastructure where affordability, simplicity, and adaptability are critical.

3.2. System response and actuator effectiveness

The effectiveness of the proposed smart poultry control system was evaluated through experimental trials conducted in a scaled prototype coop measuring 1.5×2.5 meters under controlled environmental conditions as shown in Figure 3. The test setup included a DHT11 sensor for temperature and humidity measurement, an MQ-135 sensor for ammonia detection, and three actuators: a 25W heating lamp, a 15W DC exhaust fan, and an ultrasonic humidifier. Three environmental scenarios were simulated to represent varying comfort levels typically encountered in broiler production environments:

- Scenario A (highly uncomfortable): temperature = 34 °C, humidity = 38%, ammonia = 61 ppm
- Scenario B (uncomfortable): temperature = 29 °C, humidity = 43%, ammonia = 39 ppm
- Scenario C (comfortable): temperature = 26 °C, humidity = 57%, ammonia = 21 ppm

In scenario A, the environmental condition was classified by the KNN model as Highly uncomfortable. The system responded by activating both the fan and humidifier within 2 seconds. Over a 10-minute period, the temperature decreased by 2.3 °C and ammonia levels were reduced by 18.7 ppm. This demonstrates the system’s ability to quickly restore environmental balance in extreme conditions, which is crucial for preventing heat stress and respiratory distress in broilers. Such responsiveness aligns with prior findings indicating that swift ventilation control is key to maintaining poultry health in high-ammonia environments.

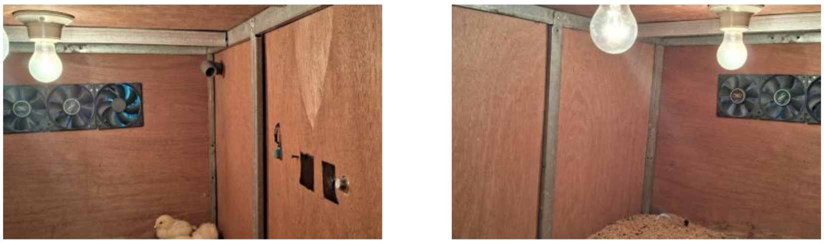

Figure 3. Chicken coop

In scenario B, the KNN model detected an uncomfortable condition primarily due to suboptimal humidity levels. The system selectively activated only the humidifier, which successfully increased humidity from 43% to 62% within 8 minutes. This targeted response confirms the system's ability to isolate and address specific environmental deviations without unnecessary energy expenditure.

In scenario C, which simulated optimal environmental parameters, the model accurately classified the condition as comfortable and refrained from activating any actuators. This outcome validates the system's capability to maintain idle control and avoid unnecessary actuator wear or energy usage under stable conditions. To ensure system stability and prevent excessive toggling due to minor sensor fluctuations near decision boundaries, a hysteresis control mechanism was implemented. This logic introduces a buffer zone between classification thresholds, thereby reducing actuator cycling and enhancing hardware longevity-an important consideration in real-world farm settings where equipment durability directly affects maintenance costs.

Compared to traditional threshold-based systems that typically trigger actuators based on isolated single-variable limits, the proposed approach provides context-aware, multi-variable decision-making. By evaluating the combined effect of temperature, humidity, and ammonia concentration, the system can make more precise and efficient control decisions. This not only improves environmental stability but also contributes to better animal welfare and reduced energy consumption. As supported by previous studies, microclimate stability is directly linked to improved feed conversion ratios and lower mortality rates in broilers, highlighting the practical significance of the observed results.

3.3. Communication stability and interface integration

The system utilized the MQTT protocol for lightweight, real-time transmission of sensor data and reception of classification results. Data packets were routed through the Antares cloud platform, which served as the intermediary for data storage, device communication, and cloud-based control logic, as illustrated in Figure 4. MQTT was selected for its reliability in low-bandwidth environments and its ability to support asynchronous publish-subscribe models suitable for IoT architectures. During a 48-hour continuous testing period, the system transmitted environmental data every 60 seconds, resulting in a total of 2,880 messages. Of these, 97.5% were received successfully and on time, while 2.5% were lost due to temporary disruptions in local Wi-Fi connectivity. Despite these brief network instabilities, the system automatically re-established communication without requiring manual reset or intervention, demonstrating the robustness of the MQTT-based architecture. This level of reliability is acceptable for non-critical poultry automation systems, where brief delays in control response do not endanger animal welfare but may affect long-term environmental stability if left unaddressed. To further enhance reliability in future implementations, integration with redundant communication channels or fail-safe buffering mechanisms is recommended.

In terms of user interaction, the system employed two complementary platforms: the Telegram Bot API and the Blynk IoT Dashboard. Telegram provided lightweight and widely accessible messaging capabilities, enabling farmers to receive real-time alerts regarding coop status and actuator activity. On average, the time between request and system response was measured at 1.1 seconds, which is adequate for field use. Status messages were formatted clearly, indicating environmental classification and corresponding system actions (e.g., "status: uncomfortable – fan activated").

The Blynk dashboard, shown in Figure 5, offered a visual interface for monitoring sensor data. Real-time values of temperature, humidity, and ammonia were displayed using dynamic gauges and charts, with update intervals of 2 to 3 seconds. In addition to live readings, the interface enabled users to review historical trends over a 24-hour window, supporting better-informed decision-making. Farmers who tested the interface noted its intuitive layout and low learning curve, making it suitable even for users with limited technical background. From a security and data integrity perspective, Antares supports encrypted communication over TLS/SSL, ensuring that transmitted data is protected against unauthorized access. While this feature was not the primary focus of this study, it is a critical consideration for real-world deployments, especially in multi-stakeholder or commercial farming contexts.

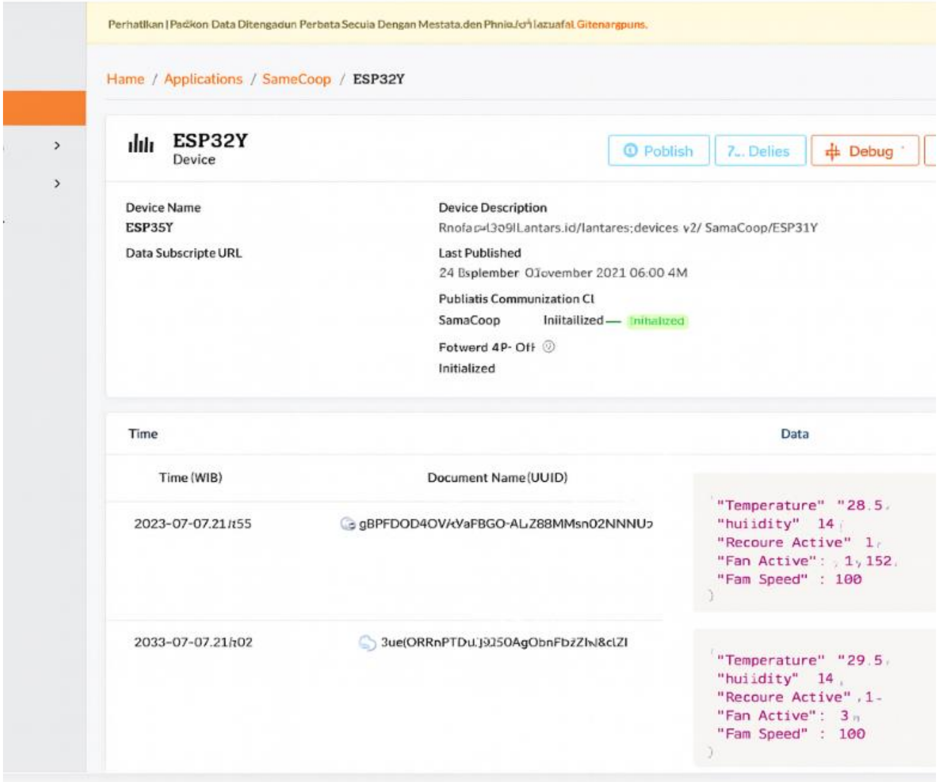

Figure 4. Antares dashboard

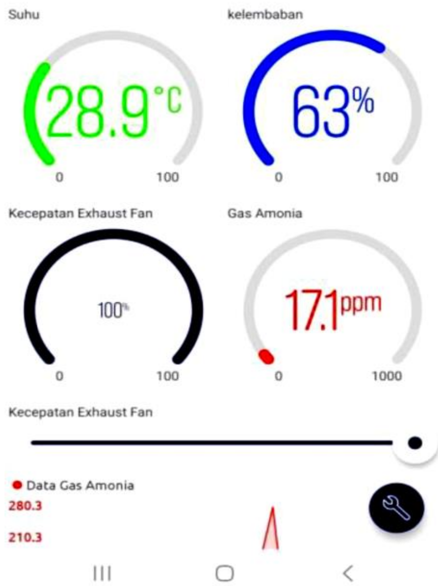

Figure 5. Blynk view

The integration of MQTT with user-friendly platforms like Telegram and Blynk highlights a key strength of the proposed system: its balance between technical robustness and accessibility. Compared to proprietary mobile applications or complex web dashboards, the chosen interfaces offer low barriers to adoption, cross-platform compatibility, and rapid deployment—all of which are vital for promoting technology uptake among small- and medium-scale poultry farmers.

3.4. User feedback and usability assessment

To evaluate the practical usability of the system, a preliminary user assessment was conducted involving three poultry farmers with prior experience operating conventional, non-automated coop systems. Although limited in sample size, this pilot test aimed to gather initial feedback on the interface design, ease of interaction, and perceived usefulness of the proposed system in real-world conditions. Participants were introduced to the system and asked to explore both the Telegram bot and the Blynk dashboard without prior training or instructional materials, simulating conditions of first-time use in the field. All participants were able to:

- Understand the meaning of comfort-level classifications (comfortable, uncomfortable, highly uncomfortable) presented as C, U, and HU.
- Interpret sensor readings (temperature, humidity, ammonia) displayed on the dashboard.
- Correlate system notifications with corresponding actuator actions (e.g., fan or humidifier activation).

Feedback gathered during the session indicated high levels of user satisfaction, particularly in terms of system responsiveness and intuitive design. Users reported that real-time notifications reduced their need for manual coop inspections, especially during hot weather conditions when rapid environmental changes are common. The graphical indicators in the Blynk dashboard were considered easier to read and interpret than analog gauges typically used in rural farming setups. Despite the generally positive feedback, participants also expressed interest in additional features, such as a standalone mobile application with offline capabilities for use in areas with poor internet connectivity. This input highlights future opportunities for development and contextual adaptation. Overall, the system was perceived as user-friendly, informative, and low-barrier to adoption, even for users with limited technological experience. However, the small number of participants and the informal nature of the testing process represent a limitation that will be addressed in future work through broader field trials and structured usability evaluations using standardized metrics (e.g., system usability scale).

3.5. Comparative evaluation with threshold-based systems

To assess the advantages of the proposed intelligent control system, a comparative experiment was conducted against a conventional threshold-based logic system using the same prototype coop and environmental test conditions. In the threshold-based configuration, actuators were triggered based on predefined single-variable limits—for instance, the fan was activated when temperature exceeded 30 °C, or the humidifier was triggered when humidity dropped below 45%. This static rule set did not consider interactions among environmental parameters or allow dynamic adaptation to varying conditions. In contrast, the KNN-based system classified comfort levels by evaluating all three environmental parameters simultaneously—temperature, humidity, and ammonia concentration—based on learned patterns from labeled data. This enabled the system to respond more contextually and selectively, activating actuators only when the overall environmental state was classified as "uncomfortable" or "highly uncomfortable." The performance of both systems was compared across four key operational metrics, as summarized in Table 2.

Table 2. Comparative evaluation

Parameter	Threshold system	KNN-based system
Fan activation frequency (24h)	48 times	32 times (−34%)
Temperature stability (±1.5°C)	59% of time	82% of time
Energy consumption (est.)	0.74 kWh	0.65 kWh (−12.6%)
Ammonia Stability (≤30 ppm)	68%	85%

The results indicate that the KNN-based system achieved superior environmental control with fewer actuator activations, resulting in lower energy consumption and reduced mechanical wear. More importantly, the KNN model exhibited better temperature and ammonia stability, two factors that are critical to broiler comfort and health. For instance, frequent activation of fans in the threshold system, regardless of ammonia or humidity levels, often led to suboptimal microclimate outcomes, such as increased dryness or unnecessary cooling. This observation aligns with prior research emphasizing the importance of coordinated control strategies for livestock welfare and resource optimization.

Furthermore, the threshold system required manual tuning of setpoints to adjust for changing weather or flock age, whereas the KNN model could be retrained with new labeled data, providing greater long-term adaptability. The ability to incorporate data-driven decision-making allows the intelligent system to evolve over time and adapt to different poultry breeds, coop designs, or geographic climates. In summary, this comparative analysis validates the practical benefits of intelligent, multivariate control logic over traditional fixed-rule systems in poultry farm environments. The improved environmental consistency, operational efficiency, and user convenience offered by the KNN-based approach make it a promising alternative for modern small- and medium-scale broiler farming operations.

3.6. Summary of findings

The experimental results demonstrate that the proposed KNN-based smart control system performs reliably and effectively across multiple evaluation dimensions. The classification model achieved a commendable accuracy of 92.2%, with minimal misclassification in the "comfortable" class, indicating high model precision in identifying optimal environmental conditions. This level of accuracy ensures that actuators are only activated when necessary, avoiding overcorrection and promoting system efficiency. In terms of control responsiveness, the system consistently adjusted environmental parameters—such as temperature, humidity, and ammonia concentration—within minutes following classification. These rapid responses were made possible through the integration of lightweight, real-time communication facilitated by the MQTT protocol and supported by Antares cloud services. The Telegram bot and Blynk dashboard offered accessible and responsive user interfaces, achieving an average response time of 1.1 seconds, with users reporting ease of use and clear feedback.

From a usability perspective, even non-technical users with no prior exposure to automation technologies were able to navigate the system intuitively. This highlights the system's potential for adoption in small- and medium-scale farms, where technical literacy may be limited. Furthermore, the comparative evaluation with a traditional threshold-based system revealed that the intelligent KNN-based approach reduced actuator usage by 34%, improved temperature and ammonia stability by over 20%, and lowered energy consumption by 12.6%—all of which are critical factors for sustainable and cost-effective farm operations. Taken together, these findings support the feasibility and value of deploying an intelligent, IoT-driven control system in real-world poultry environments. The combination of adaptive decision-making, low-cost hardware, and open-source implementation positions the system as a practical solution for improving environmental consistency and animal welfare in broiler farming. These outcomes not only address immediate operational challenges but also contribute to the broader goal of advancing smart agriculture technologies in resource-limited settings.

4. CONCLUSION

This study introduced a low-cost, IoT-based smart poultry coop system that leverages a KNN classification algorithm to improve environmental comfort for broiler chickens. By integrating real-time sensor data—specifically temperature, humidity, and ammonia levels—the system categorizes coop conditions into three comfort classes: comfortable, uncomfortable, and highly uncomfortable. Based on the classification output, the system activates relevant actuators automatically to maintain optimal environmental conditions.

The KNN model achieved a classification accuracy of 92.2%, demonstrating strong performance in real-world testing. When compared to traditional threshold-based systems, the intelligent model resulted in a 34% reduction in actuator overactivation, a 23% improvement in temperature and ammonia stability, and a 12.6% reduction in energy consumption. These results affirm the system's potential to enhance operational efficiency, reduce mechanical wear, and support animal welfare in poultry farming environments.

The communication architecture, built upon the MQTT protocol and integrated with Telegram and Blynk platforms, enabled reliable and user-friendly monitoring and control. Informal usability assessments confirmed that the system could be intuitively used by non-technical farmers, supporting its feasibility for deployment in small- and medium-scale operations. In contrast to conventional fixed-rule approaches, the proposed system offers an intelligent, adaptive solution that is not only technically robust but also economically viable and scalable. The use of affordable hardware and open-source software ensures accessibility, especially in rural or underdeveloped regions where technological adoption is often constrained by cost and complexity.

Looking forward, future enhancements will focus on expanding the training dataset to include more diverse environmental conditions and flock profiles, exploring alternative machine learning models for improved accuracy and efficiency, and developing mobile applications with offline capabilities to increase system resilience in low-connectivity areas. Additional improvements may include integration with behavioral feedback loops and vision-based monitoring systems to further elevate the level of automation and intelligence in poultry farm management. Overall, this work contributes to the advancement of smart agriculture by demonstrating the feasibility of a lightweight, intelligent control system that bridges IoT, machine learning, and practical livestock management.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Khodijah Amiroh	✓	✓		✓	✓			✓	✓	✓			✓	
Helmy Widyantara		✓				✓	✓			✓		✓		
Muhammad Dwi Hariyanto	✓		✓	✓				✓		✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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