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Research Article

IoT-Based Temperature and Humidity Monitoring and Control System for Quail Cages Using the K-Nearest Neighbors Algorithm

Anindya Rochmah Mawaddati[1], Achmad Hamdan[2]*, Muladi[3], Ihwanudin[4], Hafid Setyo Hadi[5]

[1] Department of Engineering Technology, Faculty of Vocational Studies, Universitas Negeri Malang, Indonesia; e-mail: anindya.rochmah.2105325@students.um.ac.id
[2] Department of Engineering Technology, Faculty of Vocational Studies, Universitas Negeri Malang, Indonesia; e-mail: achmad.hamdan.ft@um.ac.id
[3] Department of Engineering Technology, Faculty of Vocational Studies, Universitas Negeri Malang, Indonesia; e-mail: muladi@um.ac.id
[4] Department of Engineering Technology, Faculty of Vocational Studies, Universitas Negeri Malang, Indonesia; e-mail: m.ihwanudin.fv@um.ac.id
[5] Department of Engineering Technology, Faculty of Vocational Studies, Universitas Negeri Malang, Indonesia; e-mail: hafidsetyo.fv@um.ac.id
* Corresponding Author: achmad.hamdan.ft@um.ac.id

Abstract. The stability of the microclimate in the cage is a necessity in quail farming, since the temperature and humidity directly influence the comfort, growth, health and egg production of the animals. Manual monitoring is limited by farmer availability, reaction times, and inconsistent observations, particularly in the context of rapid environmental change. This work describes the development of an Internet of Things (IoT)-based temperature and humidity monitoring and control system with the K-Nearest Neighbors (K-NN) algorithm to categorize the quail cage environment states and to facilitate autonomous actuator management. The system was designed utilizing ESP32 microcontroller, DHT22 sensor, Incandescent bulb, Blower, Firebase real time database and a monitoring application based on Flutter. The temperature and humidity data were collected from the cage environment, identified by K-NN according to the established environmental classes and used to determine actuator responses. The experimental findings indicated that the system could monitor the cage conditions in real time and operate the lamp and blower according to the intended control logic. The DHT22 sensor produced an average temperature error of approximately 3.77% and an average humidity error of approximately 7.04%. The real-time monitoring delay ranged from 1 to 4 seconds, with an average delay of about 2 seconds. In preliminary classification testing, the K-NN results showed full agreement with manual decisions for the tested samples. These findings indicate that the developed IoT and K-NN-based system can support more efficient quail cage microclimate management and provide a practical low-cost smart farming solution for small-scale poultry farmers.

Keywords: Humidity Monitoring; Internet of Things; Quail Cage; Smart Farming; Temperature Control.

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1. Introduction

Quail farming is an important poultry agribusiness sector because it contributes to animal protein supply, household income, and rural economic development. Quails are widely cultivated due to their relatively fast production cycle, low maintenance cost, small space requirement, and high potential for egg production. These characteristics make quail farming suitable for small and medium-scale farmers, especially in rural areas where livestock activities can become an alternative source of income (Andari et al., 2018; Ta'wim, 2024). In addition, quail farming is considered economically promising because quails can begin laying eggs at a relatively young age and may produce eggs continuously when cage management is properly maintained (Amelia, 2023). Therefore, the productivity of quail farming is closely related to the quality of livestock management, particularly the stability of cage environmental conditions.

The regulation of the cage microclimate notably temperature and humidity is one of the key topics of concern in quail farming . These two environmental elements affect directly physiological comfort, feed consumption, immunological response, growth and egg output. High temperatures may produce heat stress that can decrease feed intake and production performance. Low temperatures might affect thermal comfort and demand additional heating. In addition, incorrect humidity can also raise the risk of dehydration, respiratory problems, and disease transmission (Asri & Harissatria, 2021; Rizal, 2024; Yahya & Erwanto, 2020). Thus, continual monitoring of temperature and humidity is required for the maintenance of a quail cage environment that is beneficial to quail health and productivity. In normal farming practice, farmers often check temperature and humidity manually. Manual monitoring is easy and cheap, but has many shortcomings. Observation accuracy is dependent on farmer availability, monitoring frequency and response speed. Environmental changes inside the cage can occur at any time due to exterior climatic changes, cage density, ventilation and animal activity. In the absence of farmers or late responses, cage conditions could drift away from the optimum range. This may lead to less comfort and productivity of the livestock. To eliminate manual intervention and improve the responsiveness of cage environmental management, a real-time monitoring and autonomous control system is necessary.

The IoT is widely employed in smart farming because of its sensor-based data collecting, real-time transmission, remote monitoring and autonomous control. Systems based on the Internet of Things can integrate environmental sensors, microcontrollers, cloud databases and mobile or web apps. DHT11, DHT22 and LM35 sensors have been utilized in livestock monitoring systems to measure temperature and humidity. Microcontrollers such as ESP8266 and ESP32 are also widely employed as processing and communication units (Cosi & Vargas-Cuentas, 2021; Rizal, 2024). There are several benefits of IoT such as real-time data availability, less human error, greater operational efficiency, and more flexible decision-making assistance for the farmers (Priya & Ramasamy, 2021; Zhang et al., 2020). Yet, IoT systems that just visualize sensor data may still be constrained since they are not always providing intelligent interpretation or autonomous decision-making.

Several previous studies have developed IoT-based monitoring and control systems for cage environments. Rizal (2024) developed a quail cage monitoring system using DHT11, LM35, ESP32, and the Fuzzy Sugeno method to determine lamp voltage and fan speed. The strength of fuzzy logic lies in its ability to handle gradual control decisions, but it requires carefully designed membership functions and rules. Yahya and Erwanto (2020) also applied fuzzy logic to control temperature and humidity in quail cages, showing that intelligent control methods can improve cage management. Cosi and Vargas-Cuentas (2021) developed a low-cost quail farming prototype using Arduino Nano, DHT11, and LM35 sensors. This approach was practical, but the sense of accuracy and decision-making capability remained limited. Other IoT livestock monitoring studies have focused on data acquisition and communication reliability, but not all of them integrate sensor data classification, real-time mobile monitoring, and actuator control in one system (Aleluia et al., 2023; Chairunnas, 2024).

Machine learning based classification can make IoT systems more robust by transforming sensor data into useful environmental classifications. The K-Nearest Neighbors (K-NN) algorithm is among the most interpretable and simplest of the classification methods. The K-NN classifies the new data based on the nearest training samples using a distance metric, for example, Euclidean distance (Agusta, 2007; Ulya et al., 2021). Its advantages include its simplicity of implementation, interpretability and applicability to tiny data sets. However, the performance of K-NN is dependent on the quality of the training data set, the feature scaling and the K value selected. K-NN: K-NN can be used to define quail cage conditions (normal, cold and dry, hot and humid or hot and dry) based on temperature and humidity patterns.

Based on these difficulties and research gaps, this work proposed an IoT-based temperature and humidity monitoring and control system for quail cages utilizing K-Nearest Neighbors algorithm. The system constructed in this study consists of a DHT22 sensor, ESP32 microcontroller, Firebase real-time database, Flutter-based application, Incandescent lamp, AC light dimmer, relay, and blower. The DHT22 sensor is used to get temperature and humidity data. The ESP32 is used to process data and control actuators. Firebase is used to store and synchronize data in real time. The Flutter application is used to display the monitoring information and support manual control. The K-NN method is used to classify the cage environmental conditions and assist actuator decisions.

The innovation of the present work consists in combining in a low-cost cage prototype the IoT-based real-time monitoring, mobile-based data display, K-NN environmental categorization and automatic control of actuators. Unlike monitoring-only systems, the created system not only shows the temperature and humidity measurements, but also translates them into environmental classes and activates management responses. K-NN, unlike fuzzy-based techniques, provides an instance-based classification mechanism which can be updated by expanding the training dataset.

The important contributions of this paper are summarized as follows. First, a real-time IoT-based temperature and humidity monitoring system for quail cage has been designed and developed utilizing ESP32, DHT22, Firebase and Flutter. Second, the cage environment conditions are classified using the K-NN algorithm based on the temperature and humidity data. Third, the study combines automatic control of the actuator with an incandescent lamp and a fan to help regulate the microclimate in the cage. Fourth, the system is evaluated in terms of sensor reading accuracy, real-time monitoring latency, actuator response and preliminary K-NN classification performance.

The remainder of the paper is organized as follows. Section 2 explains the study approach comprising system architecture, hardware design, software design, dataset, K-NN classification, actuator control logic and evaluation scenario. 3. Results and Discussion: In this section, the hardware and software implementation, dataset analysis, sensor testing, actuator testing, real-time monitoring performance, classification result, and system constraints are discussed. Section 4 compares the developed system with the state-of-the-art studies. Section 5 closes the work and outlines directions for future research.

2. Research Method

This section describes the research method step by step. The discussion includes research design, system architecture, hardware design, software and IoT data flow, K-NN dataset and environmental classes, actuator control logic, algorithm, and evaluation scenario. The method is presented with equations, tables, and algorithmic steps to clarify the implementation process.

Research Design

This study used a system development approach to design and implement an IoT-based prototype for monitoring and controlling quail cage temperature and humidity. The research procedure consisted of five stages: literature review, requirement analysis, system design, system implementation, and system evaluation.

The literature review was conducted to identify quail environmental requirements, IoT components, sensor characteristics, actuator control, and K-NN classification. Requirement analysis was used to determine the required input, output, hardware, software, and evaluation parameters. The system design stage included hardware architecture, software architecture, wiring design, and control logic. The implementation stage involved assembling the hardware, programming the ESP32, connecting Firebase, developing the Flutter interface, and implementing K-NN classification. The evaluation stage measured sensor accuracy, actuator response, real-time monitoring delay, and classification agreement.

System Architecture

The developed system consists of three main layers: input layer, processing and communication layer, and output layer. The input layer consists of the DHT22 sensor that measures cage temperature and humidity. The processing and communication layer consists of the ESP32 microcontroller, which reads sensor data, performs K-NN classification, controls actuators, and sends data to Firebase through Wi-Fi. The output layer consists of physical actuators and a mobile monitoring interface. The physical actuators include an incandescent lamp, AC light dimmer, relay, and blower. The mobile monitoring interface is developed using Flutter and connected to Firebase.

Fig. 1 illustrates the system architecture developed in this study. Temperature and humidity data are acquired by the DHT22 sensor and processed by ESP32. The K-NN algorithm classifies the cage condition based on the training dataset. The system then controls the lamp and blower according to the classification result and threshold rules. The data are uploaded to Firebase and displayed on the Flutter application.

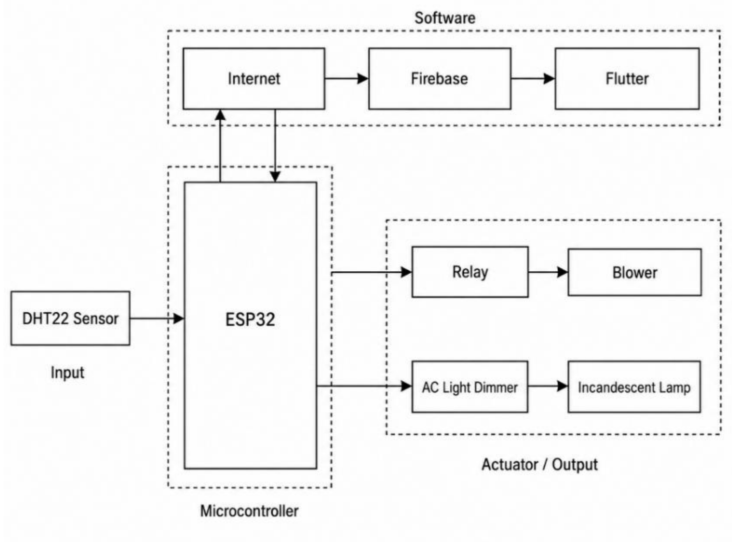

Figure 1. IoT-Based Temperature and Humidity Monitoring and Control Architecture for Quail Cages.

Hardware Design

The hardware design was developed to support automatic environmental monitoring and control. The components used in the developed system are presented in Table 1.

Table 1. Hardware Components Used in the Developed System Cited.

Component	Quantity	Function
ESP32 microcontroller	1	Main controller, sensor data processing, Wi-Fi communication, and actuator control
DHT22 sensor	1	Measuring temperature and humidity inside the cage
AC light dimmer	1	Controlling incandescent lamp intensity
Incandescent lamp	1	Heating actuator for increasing cage temperature
Relay module	1	Switching control for blower operation
Blower	1	Air circulation and humidity control
Step-down module	1	Voltage conversion for electronic components
PCB	1	Integrated circuit connection medium
Jumper cables	Several	Electrical connection between components

The DHT22 sensor was connected to ESP32 as the input device. The incandescent lamp was connected through an AC light dimmer to regulate heating intensity. The blower was connected through a relay module so that it could be turned on or off automatically. The ESP32 was selected because it supports Wi-Fi communication and provides sufficient input-output pins for an IoT-based monitoring and control system.

The pin configuration is summarized in Table 2.

Table 2. Pin Configuration of the Developed System.

ESP32 Pin	Connected Component	Function
3V3	DHT22 VCC	Sensor power supply
GND	DHT22 GND, dimmer GND, relay GND	Common ground
Pin 18	DHT22 data pin	Temperature and humidity input
Pin 22	AC light dimmer PWM	Lamp intensity control
Pin 23	AC light dimmer control pin	Lamp control signal
Pin 25	Relay input	Blower control signal
Pin 26	Relay input	Additional relay control signal

Software and IoT Data Flow

The software system consists of ESP32 embedded programming, Firebase real-time database configuration, and Flutter application development. The ESP32 program initializes the DHT22 sensor, connects to Wi-Fi, connects to Firebase, reads temperature and humidity, classifies environmental conditions using K-NN, controls the lamp and blower, and sends data to Firebase. Firebase stores temperature, humidity, classification status, lamp status, and blower status. The Flutter application retrieves data from Firebase and displays it to users in real time.

The data flow begins when ESP32 connects to the internet and Firebase. After the connection is established, the DHT22 sensor reads temperature and humidity. The readings are used as testing data for K-NN classification. The classification result and threshold rules determine the actuator's response. The lamp and blower status are updated, and all data are sent to Firebase. Users can monitor the cage condition through the Flutter application and perform manual control when needed.

Fig. 2 shows the workflow of the IoT-based monitoring and control system.

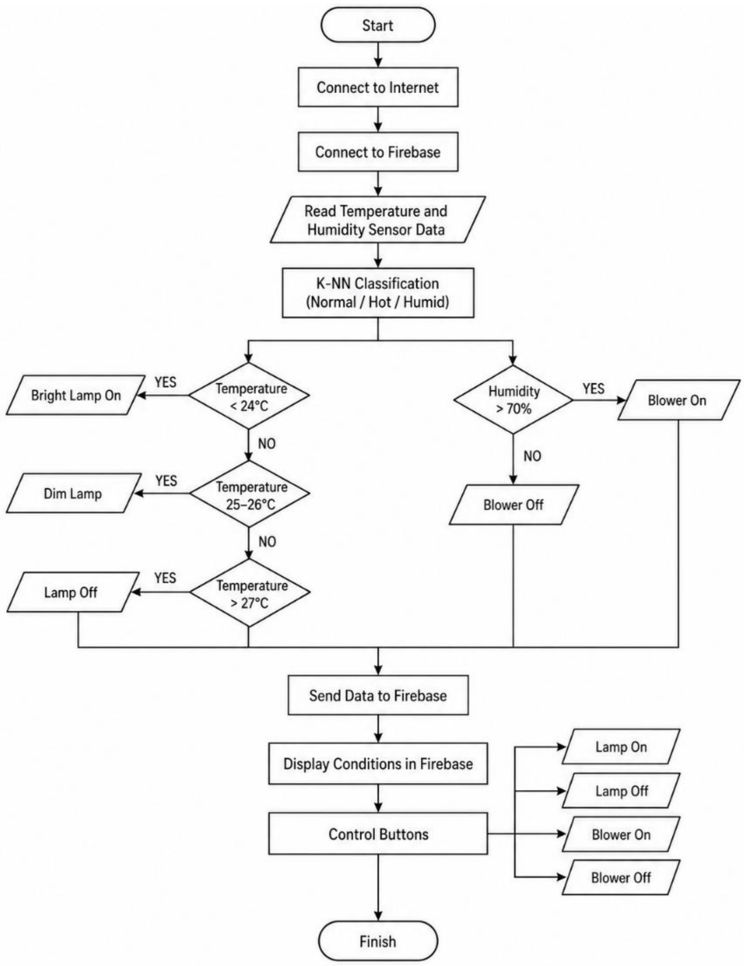

Figure 2. Workflow of the IoT-Based Monitoring and Control System.

K-NN Algorithm and Environmental Classification

The K-Nearest Neighbors algorithm was used to classify the environmental condition of the quail cage based on two input features: temperature and humidity. Each sensor reading was treated as testing data and compared with the training dataset. The Euclidean distance was used to calculate similarity between testing data and training data. Eq. (1) shows the general Euclidean distance formula.

$$\boldsymbol{d} = \sqrt{\sum_{i=1}^{p}(\boldsymbol{x}_{2i} - \boldsymbol{x}_{1i})^2} \tag{1}$$

where ($\boldsymbol{d}$) is the distance between two data points, ($\boldsymbol{x_1}$) is the training data, ($\boldsymbol{x_2}$) is the testing data, and ($\boldsymbol{p}$) is the number of features. Because this study uses two features, temperature and humidity, the equation can be simplified as shown in Eq. (2).

$$\boldsymbol{d} = \sqrt{(\boldsymbol{T_{test}} - \boldsymbol{T_{train}})^2 + (\boldsymbol{H_{test}} - \boldsymbol{H_{train}})^2} \tag{2}$$

where ($\boldsymbol{T_{test}}$) and ($\boldsymbol{H_{test}}$) are temperature and humidity values from the sensor, while ($\boldsymbol{T_{train}}$) and ($\boldsymbol{H_{train}}$) are temperature and humidity values from the training dataset. The nearest neighbors are then selected and used to determine the environmental class.

In this draft, (K = 3) is used as the nearest-neighbor voting parameter. This value should be confirmed based on the final source code before journal submission. The majority class among the nearest neighbors was used as the classification result. The classification result was then used as one of the bases for determining cage status and actuator response.

2.6. K-NN Dataset and Environmental Classes

The K-NN classification used two input features: temperature and humidity. The training dataset consisted of 24 data points with environmental class labels. The dataset was designed to represent various cage conditions, including cold and dry, slightly cold and normal, normal, slightly hot and humid, hot and humid, hot and normal, hot and dry, normal and humid, slightly cold and humid, and normal and normal. The dataset is shown in Table 3.

Table 3. Training Dataset for K-NN-Based Environmental Classification.

No.	Temperature (°C)	Humidity (%)	Class
1	22.0	50.0	Cold and Dry
2	22.5	55.0	Cold and Dry
3	23.0	60.0	Slightly Cold and Normal
4	23.5	63.0	Slightly Cold and Normal
5	24.0	65.0	Normal
6	24.5	66.0	Normal
7	25.0	68.0	Normal
8	25.5	70.0	Normal
9	26.0	72.0	Normal
10	26.5	74.0	Slightly Hot and Humid
11	27.0	75.0	Slightly Hot and Humid
12	27.5	78.0	Slightly Hot and Humid
13	28.0	80.0	Hot and Humid
14	28.5	82.0	Hot and Humid
15	29.0	83.0	Hot and Humid
16	30.0	85.0	Hot and Humid
17	30.5	70.0	Hot and Normal
18	31.0	65.0	Hot and Normal
19	32.0	60.0	Hot and Dry
20	33.0	55.0	Hot and Dry
21	25.0	80.0	Normal and Humid
22	24.0	75.0	Slightly Cold and Humid
23	26.0	60.0	Normal and Normal
24	28.0	65.0	Hot and Normal

Each sensor reading was compared with the training dataset using Eq. (2). The three nearest data points were selected because this draft uses (K = 3). The final value of K should be confirmed based on the final source code before journal submission. The majority class among the nearest neighbors was used as the classification result.

Actuator Control Logic

The actuator control logic was developed based on temperature and humidity thresholds. The lamp was used to increase or maintain cage temperature, while the blower was used to improve air circulation and reduce excessive humidity. The control rules are presented in Table 4.

Table 4. Actuator Control Rules.

Parameter condition	Actuator response	Purpose
Temperature < 24°C	Lamp on with high intensity	Increase cage temperature
Temperature 25°C–26°C	Lamp dimmed	Maintain moderate heating
Temperature > 27°C	Lamp off	Prevent excessive heating
Humidity > 70%	Blower on	Improve air circulation and reduce humidity
Humidity ≤ 70%	Blower off	Maintain stable condition

The control logic allows the system to respond automatically to environmental changes. When the temperature is low, the lamp is turned on. When the temperature is high, the lamp is turned off. When humidity exceeds the threshold, the blower is activated. This mechanism is intended to reduce manual intervention and maintain cage microclimate stability.

Algorithm/Pseudocode

Algorithm 1 describes the IoT-based monitoring and control process using K-NN.

Algorithm 1. IoT-Based Quail Cage Monitoring and Control Using K-NN

INPUT: Temperature (T), humidity (H), K-NN training dataset, control thresholds
OUTPUT: Environmental class, lamp status, blower status, real-time monitoring data

1: Initialize ESP32, DHT22 sensor, Firebase connection, lamp actuator, and blower actuator
2: Connect ESP32 to Wi-Fi
3: Connect ESP32 to Firebase real-time database
4: Read temperature (T) and humidity (H) from DHT22
5: Set sensor reading as testing data (X_{test} = (T, H))
6: For each training data (X_{train}), calculate Euclidean distance using Eq. (2)
7: Sort all training data based on the smallest distance
8: Select the nearest neighbors based on (K = 3)
9: Determine the environmental class using majority voting
10: If (T < 24^\circ C), turn on the lamp with high intensity
11: Else if (25^\circ C \leq T \leq 26^\circ C), dim the lamp
12: Else if (T > 27^\circ C), turn off the lamp
13: If (H > 70%), turn on the blower
14: Else turn off the blower
15: Send temperature, humidity, class, lamp status, and blower status to Firebase
16: Display real-time data on the Flutter application
17: Check manual control input from the Flutter application
18: If manual control is activated, update actuator status based on user command
19: Repeat the process continuously

Evaluation Scenario

The evaluation was conducted to measure sensor accuracy, actuator response, real-time monitoring performance, and K-NN classification agreement. Sensor readings were compared with reference instruments, and relative error was calculated using Eq. (3).

$$\text{Error}(\%) = \frac{|X_i - X_p|}{X_p} \times \mathbf{100\%} \quad (3)$$

where (X_i) is the sensor reading and (X_p) is the reference value. Real-time monitoring performance was evaluated using the delay formula in Eq. (4).

$$\text{Delay} = \boldsymbol{t}_{\text{firebase}} - \boldsymbol{t}_{\text{physical}} \tag{4}$$

where (t_{firebase}) is the Firebase update time and (t_{physical}) is the physical change time. Classification accuracy was calculated using Eq. (5).

$$\text{Accuracy}(\%) = \frac{\boldsymbol{N}_{\text{correct}}}{\boldsymbol{N}_{\text{total}}} \times \mathbf{100\%} \tag{5}$$

where (N_{correct}) is the number of correctly classified samples and (N_{total}) is the total number of tested samples. These equations were used to evaluate whether the developed system could monitor environmental data, classify cage conditions, transmit data in real time, and control actuators automatically.

3. Results and Discussion

This section presents the results and discussion of the developed system. The discussion includes hardware and software implementation, dataset use, initial data analysis, sensor testing, actuator testing, real-time monitoring performance, K-NN classification, cage condition evaluation, and limitations.

System Implementation

The system was implemented using ESP32, DHT22, Firebase, Flutter, an incandescent lamp, an AC light dimmer, a relay module, and a blower. The DHT22 sensor measured temperature and humidity. The ESP32 processed sensor data, performed K-NN classification, controlled actuators, and sent data to Firebase. Firebase stored real-time data, while the Flutter application displayed temperature, humidity, classification status, lamp status, and blower status.

Fig. 3 shows the prototype implementation of the IoT-based quail cage monitoring and control system.

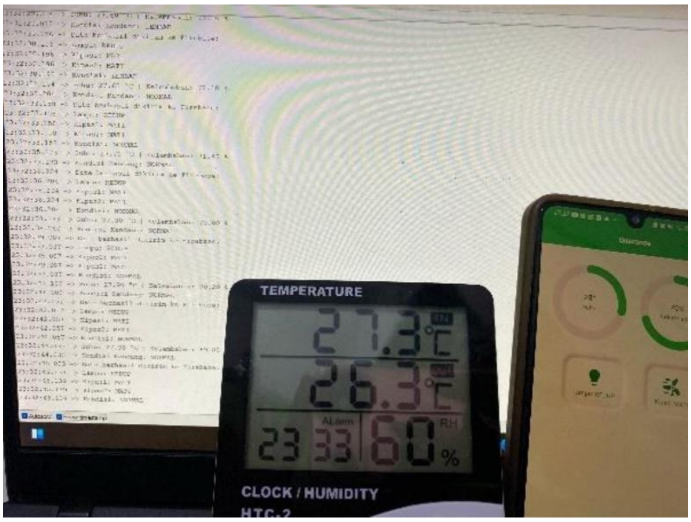

Figure 3. Prototype Implementation of the IoT-Based Quail Cage Monitoring and Control System.

The implementation confirmed that the hardware and software components could be integrated into a functional smart farming prototype. ESP32 successfully performed sensor reading, actuator control, and real-time data transmission. This result indicates that a low-cost IoT device can be used to support quail cage microclimate management.

Initial Data Analysis and Dataset Source

The K-NN dataset used in this study consisted of 24 temperature and humidity data points with predefined class labels. The dataset was designed based on environmental categories relevant to quail cage conditions. The two main features used in the classification process were temperature and humidity. The use of two features makes the classification process simple and suitable for implementation on a microcontroller-based system.

The dataset distribution shows that the environmental classes represent several condition combinations, such as cold and dry, normal, hot and humid, hot and dry, and normal and humid. This distribution allows the K-NN algorithm to classify sensor readings into meaningful cage conditions. However, because the dataset is still limited, classification results should be interpreted as preliminary. A larger dataset is needed to represent wider environmental variations and improve classification robustness.

Sensor Reading Accuracy

Sensor accuracy was tested by comparing the DHT22 readings with reference measurements obtained from a thermometer and hygrometer. The test was conducted at five different observation times. Table 5 presents the sensor accuracy results.

Table 5. Sensor Reading Accuracy Test

No	Time	DHT22 Temperature (°C)	Reference Temperature (°C)	Temperature Error (%)	DHT22 Humidity (%)	Reference Humidity (%)	Humidity Error (%)
1	08:00	25.4	24.8	2.42	78	81	3.70
2	09:20	30.4	29.8	2.01	85	88	3.41
3	12:15	27.5	26.4	4.17	73	89	17.98
4	18:25	26.9	25.7	4.67	84	87	3.45
5	20:00	26.6	25.2	5.56	70	75	6.67

The temperature error ranged from 2.01% to 5.56%, with an average error of approximately 3.77%. This result indicates that DHT22 provides acceptable temperature readings for a low-cost cage monitoring prototype. The humidity error ranged from 3.41% to 17.98%, with an average error of approximately 7.04%. The highest humidity error occurred in the third test, where the DHT22 reading was 73% and the reference hygrometer showed 89%.

The relatively high humidity error may be caused by sensor response time, sensor placement, airflow distribution, or temporary environmental changes during measurement. Since K-NN classification depends directly on sensor readings, measurement error may affect classification results, especially when the data are near class boundaries. Therefore, calibration, better sensor placement, and data filtering are recommended for future development.

Automatic Actuator Control Test

The automatic actuator control test evaluated whether the lamp and blower responded appropriately to environmental conditions. The lamp was controlled based on temperature, while the blower was controlled based on humidity. The results are shown in Table 6.

Table 6. Automatic Actuator Control Test

No	Time	Temperature (°C)	Humidity (%)	Lamp Status	Blower Status
1	08:00	25.4	78	On	Off
2	09:20	30.1	85	Off	On
3	12:15	29.2	82	Off	On
4	18:25	26.9	75	Off	Off
5	20:00	25.6	60	On	Off

The results show that the actuator control mechanism generally followed the intended control logic. When the temperature was relatively high, the lamp was turned off to prevent additional heating. When humidity reached 85% and 82%, the blower was turned on to improve air circulation. When the temperature was lower, the lamp was turned on to provide heating.

However, the fourth test shows that the blower remained off at 75% humidity. This result indicates that the final implementation should clarify whether the humidity threshold was strictly implemented, whether manual control influenced the actuator status, or whether a hysteresis mechanism was applied. This finding is important because actuator consistency affects system reliability. A future version of the system should apply hysteresis control, such as turning on the blower above 75% humidity and turning it off only when humidity falls below 70%, to reduce unstable switching near the threshold.

Fig. 4 shows the lamp activation condition during actuator testing.

Figure 4. Lamp Activation Condition During the Actuator Control Test.

Real-Time Monitoring Performance

Real-time monitoring performance was evaluated by measuring the delay between physical changes and Firebase updates. Table 7 presents the monitoring delay results.

Table 7. Real-Time Monitoring Delay Test.

No.	Physical Change Time	Firebase Update Time	Delay (s)
1	12:00	12:02	2
2	12:15	12:19	4
3	12:24	12:26	2
4	13:04	13:05	1
5	13:30	13:31	1

The delay ranged from 1 to 4 seconds, with an average delay of approximately 2 seconds. This result indicates that the system can transmit data to Firebase with relatively low latency. In quail cage monitoring, a delay of 1–4 seconds is acceptable because temperature and humidity changes generally do not require millisecond-level response. The system can still provide near real-time information for farmers through the Flutter application.

The delay variation may be influenced by Wi-Fi signal quality, Firebase communication latency, ESP32 processing time, and DHT22 reading interval. The DHT22 sensor also has a limited sampling rate. Therefore, the overall monitoring speed depends on both sensor and network performance. Future improvements may include optimizing data transmission intervals, improving connection stability, and adding local buffering to reduce data loss when internet connection is unstable.

Fig. 5 shows the real-time monitoring interface displayed through Firebase and Flutter.

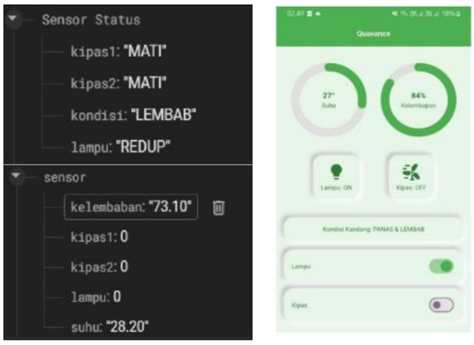

Figure 5. Real-Time Monitoring Interface Displayed Through the Flutter Application and Firebase Database.

K-NN Classification Result

The K-NN classification test evaluated whether the algorithm could classify cage environmental conditions based on temperature and humidity. The system classification results were compared with manual decisions. Table 8 presents the classification test results.

Table 8. K-NN Classification Test.

No.	Temperature (°C)	Humidity (%)	K-NN prediction	Agreement with manual decision
1	28.5	60	Hot and Dry	Yes
2	34.0	50	Hot and Dry	Yes
3	30.5	65	Hot and Normal	Yes
4	25.0	85	Cold and Humid	Yes

The results show full agreement between the K-NN prediction and manual decisions for the tested samples. This indicates that the K-NN algorithm could classify the tested temperature and humidity conditions according to the predefined environmental classes. The algorithm successfully identified hot and dry, hot and normal, and humid conditions based on the nearest training data.

However, this result should be interpreted as preliminary evidence rather than final model generalization. The number of testing samples was limited and did not represent all possible cage conditions. Machine learning classification performance depends on the diversity and representativeness of training and testing data. Therefore, further validation using a larger dataset, confusion matrix, repeated testing, and cross-validation is needed to confirm the robustness of the K-NN model.

Evaluation of Cage Environmental Conditions

The overall system effectiveness was evaluated by observing whether the system could identify cage conditions and support environmental control during several observation periods. Table 9 presents the evaluation results.

Table 9. Evaluation of cage environmental conditions.

No	Observation time	Temperature (°C)	Humidity (%)	Control status	Description
1	08:00	29.0	60	Normal	Stable
2	10:16	30.2	58	Normal Stable	Stable
3	12:14	32.5	55	Hot	Temperature increased
4	14:00	33.8	53	Hot	High temperature
5	16:25	31.0	57	Normal	Temperature decreased

The results show that the system detected changes in cage temperature and classified the condition accordingly. At 08:00 and 10:16, the system classified the cage as normal and stable. At 12:14 and 14:00, the temperature increased to 32.5°C and 33.8°C, and the system classified the condition as hot. At 16:25, the temperature decreased to 31.0°C, and the system classified the condition as normal.

The humidity values ranged from 53% to 60%, indicating relatively dry conditions compared with the humidity threshold used for blower activation. Therefore, the current actuator configuration is more suitable for reducing excessive humidity than increasing low humidity. If the target humidity range for the observed quail age requires higher humidity, a humidifier or misting system should be added in future development.

Discussion of Main Findings

The results show several important findings. First, the developed system successfully integrates sensing, classification, cloud database, mobile monitoring, and actuator control in one IoT prototype. This confirms that ESP32, DHT22, Firebase, and Flutter can be combined to create a low-cost smart farming system for quail cage management.

Second, K-NN provides an interpretable classification mechanism for identifying cage environmental conditions. Compared with simple threshold-based monitoring, K-NN can classify sensor readings into more meaningful condition categories based on similarity to training data. This makes the system more informative because farmers can see not only numerical values but also environmental status.

Third, actuator testing shows that automatic control is feasible, but the threshold logic still needs refinement. A simple threshold-based actuator mechanism may produce inconsistent behavior near boundary values. Therefore, hysteresis control, moving average filtering, and more detailed environmental rules should be considered.

Fourth, the system is practically relevant for small-scale farmers because it uses accessible components and supports remote monitoring. The combination of automatic and manual control provides operational flexibility. Farmers can allow the system to work automatically while still being able to intervene through the mobile application.

Limitations

Several limitations should be acknowledged. First, the K-NN testing dataset was still limited, so the classification result should be interpreted as preliminary agreement with manual decisions. Second, one humidity measurement showed a relatively high error, indicating the need for sensor calibration and improved sensor placement. Third, the system was evaluated within a limited observation period and did not measure long-term biological outcomes such as egg production, feed conversion, growth rate, or mortality. Fourth, the current actuator configuration mainly supports heating and ventilation, but it does not include active cooling or humidification.

Future work should expand the dataset, validate different K values, compare K-NN with other algorithms, improve sensor accuracy, and conduct long-term testing in real farming environments.

4. Comparison

Comparison with state-of-the-art is important to show the measurable contribution of the system developed in this study. Table 10 compares the developed system with previous studies based on sensor type, microcontroller, decision method, monitoring platform, control output, and main contribution.

Table 10. Comparison Between the Developed System and Previous Studies.

Study	Sensor	Microcontroller	Decision method	IoT / Monitoring Platform	Control Output
Cosi and Vargas-Cuentas (2021)	DHT11 and LM35	Arduino Nano	Rule-based	Prototype monitoring	Environmental monitoring
Yahya and Erwanto (2020)	Temperature and humidity sensors	Microcontroller-based system	Fuzzy logic	Cage control system	Temperature and humidity control
Rizal (2024)	DHT11 and LM35	ESP32	Fuzzy Sugeno	IoT-based monitoring	Lamp voltage and fan speed control

Chairunnas (2024)	Environmental sensors	IoT device	Optimization-based monitoring	IoT-based livestock monitoring	Monitoring-oriented system
This study	DHT22	ESP32	K-Nearest Neighbors	Firebase real-time database and Flutter application	Incandescent lamp, dimmer, relay, and blower control

The comparison shows that previous studies have successfully applied IoT technology and intelligent control methods to livestock or quail cage environments. Cosi and Vargas-Cuentas (2021) demonstrated the feasibility of using low-cost sensors for quail farming monitoring. Yahya and Erwanto (2020) and Rizal (2024) showed that fuzzy logic can be used for temperature and humidity control. Chairunnas (2024) emphasized IoT optimization for livestock monitoring.

Compared with these studies, the developed system provides several measurable differences. First, it uses DHT22, which provides integrated temperature and humidity measurement with better capability than DHT11. Second, it uses ESP32, which supports Wi-Fi communication and actuator control in one low-cost controller. Third, it integrates Firebase and Flutter to provide real-time mobile monitoring. Fourth, it applies K-NN to classify cage environmental conditions based on temperature and humidity patterns.

The main contribution of this study is the integration of sensing, cloud communication, mobile monitoring, K-NN classification, and actuator control into a single prototype. While previous systems often focused on monitoring or fuzzy-based control, the developed system classifies environmental conditions and supports automatic control using an instance-based machine learning approach. This makes the system more informative because the user receives environmental status, not only raw sensor values.

From the performance perspective, the system produced an average temperature error of approximately 3.77%, an average humidity error of approximately 7.04%, and an average real-time monitoring delay of about 2 seconds. In preliminary testing, K-NN classification showed full agreement with manual decisions for the tested samples. These results indicate that the developed system is feasible for real-time quail cage monitoring and control. However, larger datasets and long-term trials are needed to strengthen the classification and system reliability.

Overall, this study contributes to the development of low-cost smart farming technology by combining IoT and K-NN classification for quail cage microclimate management.

5. Conclusions

This study developed an IoT-based temperature and humidity monitoring and control system for quail cages using the K-Nearest Neighbors algorithm. The system integrated an ESP32 microcontroller, DHT22 sensor, Firebase real-time database, Flutter-based application, incandescent lamp, AC light dimmer, relay module, and blower. The system was able to acquire temperature and humidity data, classify environmental conditions, transmit data in real time, and control actuators automatically according to predefined rules.

The experimental results showed that the system could support real-time quail cage microclimate monitoring. The DHT22 sensor produced an average temperature error of approximately 3.77% and an average humidity error of approximately 7.04%. The monitoring delay ranged from 1 to 4 seconds, with an average delay of about 2 seconds. In preliminary testing, the K-NN classification results showed full agreement with manual decisions for the tested samples. These findings indicate that the integration of IoT and K-NN can provide a practical and interpretable smart farming solution for small-scale quail cage management.

The findings support the research objective by showing that the developed system can monitor environmental data, classify cage conditions, and control actuators automatically. The contribution of this study lies in the integration of sensing, real-time cloud communication, mobile monitoring, K-NN-based classification, and actuator control in a low-cost prototype. The system can help reduce dependency on manual observation and improve response time in cage environmental management.

This study has several limitations, including a limited K-NN testing dataset, the need for sensor calibration, and the absence of long-term biological evaluation related to quail productivity. Future research should expand the dataset, validate different K values, compare

K-NN with other classification methods, and conduct long-term testing in real quail farming environments. Additional features such as alarm notifications, historical data visualization, higher-precision sensors, active cooling, humidification control, and renewable energy support can be added to improve system reliability and practical implementation.

References

Agusta, Y. (2007). K-Means penerapan permasalahan dan metode terkait. *Jurnal Sistem dan Informatika, 3*.

Aleluia, V., Soares, V., Caldeira, J., & Gaspar, P. (2023). Livestock monitoring prototype implementation and validation. *Revista de Informática Teórica e Aplicada, 30*(1), 53–65. https://doi.org/10.22456/2175-2745.127207

Amelia, M. (2023). Peningkatan bobot badan burung puyuh (*Coturnix coturnix japonica*) melalui suplementasi IGP herbal. *Jurnal Nutrisi Ternak Tropis, 6*(2), 83–89. https://doi.org/10.21776/ub.jnt.2023.006.02.2

Andari, A., Enisa, E., Wulandari, R., & Suci, D. (2018). Efek suplementasi "jamu rempah" pada puyuh (*Coturnix coturnix japonica*) terhadap performa dan kadar kolesterol telur. *Jurnal Ilmu Nutrisi dan Teknologi Pakan, 16*(2), 34. https://doi.org/10.29244/jintp.16.2.34-41

Asri, A., & Harissatria, H. (2021). Pengaruh suhu lingkungan di Kota Solok terhadap suhu rektal, konsumsi pakan dan konsumsi air minum burung puyuh (*Coturnix coturnix japonica*). *Jurnal Peternakan Mahaputra, 1*(2), 60–67. https://doi.org/10.36665/jpm.v1i2.78

Aulia, L. M., Wibowo, S. A., & Vendyansyah, N. (2021). Penerapan IoT pada rancang bangun sistem miniatur robot pemadam api untuk membantu proses evaluasi pra evakuasi. *JATI (Jurnal Mahasiswa Teknik Informatika)*, 257–259. https://doi.org/10.36040/jati.v5i1.3307

Chairunnas, A. (2024). Optimization of livestock monitoring system in outdoor based on Internet of Things (IoT). *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer, 9*(2), 323–329. https://doi.org/10.33480/jitk.v9i2.5312

Cosi, S., & Vargas-Cuentas, N. (2021). Prototype of a system for quail farming with Arduino Nano platform, DHT11 and LM35 sensors, in Arequipa, Peru. *International Journal of Emerging Technology and Advanced Engineering, 11*(11), 140–146. https://doi.org/10.46338/ijetae1121_16

Damayanti, A. (2024). Sistem informasi administrasi kependudukan dengan algoritma C5.0 untuk klasifikasi penerima Program Keluarga Harapan (PKH). *JATI (Jurnal Mahasiswa Teknik Informatika, 8*(1), 63–68. https://doi.org/10.36040/jati.v8i1.8720

Efendi, Y. (2018). Internet of Things (IoT) sistem pengendalian lampu menggunakan Raspberry Pi berbasis mobile. *Jurnal Ilmiah Ilmu Komputer, 4*(2), 21–27.

Malaric, R. (2011). *Instrumentation and measurement in electrical engineering*. Universal-Publishers.

Mudjanarko, S. W., Winardi, S., & Limantara, A. D. (2017). Pemanfaatan Internet of Things (IoT) sebagai solusi manajemen transportasi kendaraan sepeda motor. *Prosiding Seminar Nasional Aplikasi Teknologi Prasarana Wilayah X (ATPW)*. https://doi.org/10.17605/OSF.IO/6UE4B

Nysa, J. (2023). Perbandingan jarak Euclidean, Manhattan, Chebyshev pada klasifikasi status gizi balita menggunakan metode K-Nearest Neighbors (K-NN). *JATI (Jurnal Mahasiswa Teknik Informatika, 7*(4), 2443–2450. https://doi.org/10.36040/jati.v7i4.7544

Priya, O., & Ramasamy, S. (2021). Impact of Internet of Things (IoT) in smart agriculture. https://doi.org/10.3233/APC210176

Rizal, M. (2024). Sistem pemantau suhu dan kelembaban kandang puyuh menggunakan metode logika fuzzy Sugeno berbasis Internet of Things. *Jurnal Fasilkom, 14*(1), 242–249. https://doi.org/10.37859/jf.v14i1.6977

Saptadi, A. H. (2014). Perbandingan akurasi pengukuran suhu dan kelembaban antara sensor DHT11 dan DHT22. *JURNAL INFOTEL: Informatika Telekomunikasi Elektronika, 6*(2), 49. https://doi.org/10.20895/infotel.v6i2.16

Shahid, N., & Aneja, S. (2017). Internet of Things: Vision, application areas and research challenges. In *International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)* (pp. 583–587).

Siagian, C. (2024). Sistem pemantauan suhu, kelembaban, cahaya, dan pH air pada rumah walet berbasis Internet of Things. *Journal of Telecommunication Electronics and Control Engineering (JTECE), 6*(1), 1–12. https://doi.org/10.20895/jtece.v6i1.988

Suprijatna, E., Atmomarsono, U., & Kartasudjana, R. (2005). *Ilmu dasar ternak unggas*. Penebar Swadaya.

Ta'wim, A. (2024). Kelayakan usaha ternak burung puyuh di Kecamatan Prambon Kabupaten Nganjuk. *JINTAN: Jurnal Ilmiah Pertanian Nasional, 4*(1), 61–69. https://doi.org/10.30737/jintan.v4i1.5290

Ulya, S., Soeleman, M., & Budiman, F. (2021). Optimasi parameter K pada algoritma K-NN untuk klasifikasi prioritas bantuan pembangunan desa. *Techno.Com, 20*(1), 83–96. https://doi.org/10.33633/tc.v20i1.4215

Yahya, M., & Erwanto, D. (2020). Design of temperature and humidity control systems in quail puppies cages using fuzzy logic method. *JEEE-U (Journal of Electrical and Electronic Engineering-UMSIDA), 4*(1), 42–56. https://doi.org/10.21070/jeeeu.v4i1.31042

Zhang, X., Cao, Z., & Wei, D. (2020). Overview of edge computing in the agricultural Internet of Things: Key technologies, applications, challenges. *IEEE Access, 8*, 141748–141761. https://doi.org/10.1109/ACCESS.2020.3013005