DOI: doi.org/10.58797/cser.040105

IoT and Edge AI for Quail Environmental Monitoring and Stress-Related Behaviour Classification

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Abstract

Temperature and humidity readings can show changes inside a quail cage, but they do not tell us how the birds are responding to those conditions. This study developed a low-cost monitoring system that combines environmental sensing with image-based analysis of quail behaviour. A DHT22 sensor measured cage temperature and humidity, while an ESP32 collected and transmitted the readings. A Raspberry Pi 4 processed images captured by a USB camera and ran a Convolutional Neural Network (CNN) based on MobileNet to classify quail behaviour into three operational categories: Normal, Stress, and Aggressive. Environmental readings and classification results were sent through MQTT, stored in a MySQL database, and displayed together on a web dashboard. The system also generated an alert when an abnormal condition was detected. In five comparisons with reference instruments, the DHT22 showed average errors of 0.36% for temperature and 0.38% for humidity. The MobileNet model reached an aggregate validation accuracy of 91.3% on 1,200 labelled images. The average time from image capture to alert delivery was 4.7 seconds. These results show that environmental data and behavioural classification can be processed together on a Raspberry Pi-based platform under the tested conditions. The system was developed for quail monitoring, but its combination of

Received: 7 January 2026
Revised: 31 March 2026
Accepted: 10 April 2026
Published: 12 April 2026
Issued: 30 April 2026

Current Steam and Education Research
e-ISSN: 3025-8529

sensors, real-time data, IoT communication, and image classification could also be used as a practical context for interdisciplinary learning.

Keywords: computer vision, edge AI, Internet of Things, quail behaviour, technology-enhanced learning

INTRODUCTION

Internet of Things (IoT) and artificial intelligence are making it possible to monitor livestock housing more continuously. Sensors can record temperature, humidity, air quality, and other cage conditions throughout the day, while connected platforms allow the data to be checked remotely and can send alerts when conditions change (Elwakeel, 2025; Modak et al., 2025; Provolo et al., 2025). This changes monitoring from occasional checks to a continuous flow of environmental data. However, collecting more data does not automatically make a monitoring system useful in practice. Recent reviews still identify reliability, interoperability, and limited field testing as important problems when IoT systems are used in agriculture (Shahab et al., 2024; Nsabiyeze et al., 2025).

For quails, temperature and humidity are especially important because changes in the cage environment can affect how the birds behave. Heat stress, for example, has been linked to changes in feeding, resting, movement, social behaviour, welfare, and productivity (Batool et al., 2023). This means that sensor readings can describe the environment, but they cannot fully show how the birds are responding to it. Studies in poultry have found that changes in ambient temperature can occur alongside changes in activity and spatial behaviour, although the response is not always the same because it can vary with age, housing conditions, and the level of heat exposure (Duenk et al., 2024; Oso et al., 2025). For this reason, temperature and humidity readings are more useful when they are considered together with behavioural observations rather than treated on their own as evidence that a bird is under physiological stress.

Behaviour is still commonly checked by direct observation, which takes time, depends on the observer, and cannot easily be maintained throughout the day. Computer vision provides another way to observe birds without requiring a person to watch the cage continuously. Deep-learning models have already been used to detect, track, and classify poultry activity and welfare-related behaviour, including models that run on edge devices so that images can be processed close to where they are captured (Cakic et al., 2023; Campbell et al., 2024; Nasiri et al., 2024; Tong et al., 2024). Even so, behaviour classification remains difficult outside controlled conditions. Birds may overlap in an image, lighting can change, similar behaviours may be difficult to separate, and model performance depends strongly on the quality and range of the training data (Bhujel et al., 2025; Merenda et al., 2024; Paneru et al., 2026; Yang, Bist, Paneru, Liu, et al., 2024).

The remaining gap is therefore not the absence of IoT sensors or computer vision, but the limited integration of cage-environment data and bird-behaviour information within the same monitoring process. Environmental-monitoring studies commonly focus on sensor values and control, whereas vision studies commonly focus on image-based detection or behaviour recognition. Smart-agriculture reviews show that image classification can be integrated with IoT through edge, cloud, or hybrid architectures, but many implementations remain application-specific and experimental (Restrepo-Arias et al., 2024). For quail farming in particular, comparatively little work has documented a low-cost workflow in which microclimate measurements and stress-related behavioural categories are processed together, stored in the same data stream, visualised on one dashboard, and used to trigger a contextual alert. The present study addresses this integration problem rather than claiming a new behavioural or physiological definition of stress.

This study developed an IoT and edge-AI platform that combines temperature and humidity sensing with image-based classification of quail behaviour. The DHT22 and ESP32 provide environmental data, while a Raspberry Pi 4 runs MobileNet inference locally on images captured by a USB camera. MQTT connects the sensing and edge-computing components, MySQL stores the records, and a web dashboard presents environmental and behavioural outputs together. In this manuscript, the labels Normal, Stress, and Aggressive refer to operational image-classification categories used by the model; they are not presented as a physiological diagnosis of stress.

The system also has potential relevance to STEAM and technology-enhanced learning because it brings environmental science, animal welfare, electronics, programming, networking, data visualisation, and artificial intelligence into one authentic problem. IoT-based learning ecosystems can support data-driven STEM activity, while authentic datasets can help learners work with the uncertainty and interpretation demands of real scientific data (Benita et al., 2021; Kjelvik & Schultheis, 2019). Recent AIoT learning research also shows how connected sensors and AI can be organised within project-based STEAM experiences (Cheng et al., 2025). This educational potential is considered as an implication of the platform, not as an outcome tested in the present engineering study.

The main contributions of this research are as follows:

1. An integrated low-cost IoT architecture that combines DHT22 sensing, ESP32 data acquisition, Raspberry Pi edge computing, MQTT communication, database storage, and a web dashboard for quail-cage monitoring.
2. Local MobileNet inference on a Raspberry Pi for classification of three operational behavioural categories without cloud inference.
3. A shared monitoring workflow that places environmental readings and image-based behavioural outputs in the same dashboard so that they can be interpreted together rather than as isolated signals.
4. A proof-of-concept test of the complete system, including DHT22 readings against reference instruments, the MobileNet validation accuracy recorded in the completed experiment, dashboard operation, and the time from image capture to alert delivery.

The evaluation therefore shows what the system could do under the conditions tested in this study. It does not establish that the behavioural classes provide a clinical diagnosis of stress or that the same performance would be obtained in other cages or farm conditions. The study also did not test the platform with learners, so no claim is made about its educational effectiveness.

METHOD

This study used an experimental engineering approach to build and evaluate an IoT-based environmental monitoring and stress-related behaviour classification system for quail farming. The work followed five stages: requirement analysis, hardware and software development, machine-learning model preparation, system integration, and performance evaluation.

Materials

The system combined sensing, processing, communication, and monitoring components. A DHT22 sensor measured temperature and humidity inside the cage, while an ESP32 collected the sensor readings. A Raspberry Pi 4 served as the edge computing device and processed the images captured by a USB camera. These devices were connected through a Wi-Fi network, with MQTT used to transfer data between the ESP32 and the Raspberry Pi. A power supply supported continuous operation of the system.

The software was selected according to these functions. The ESP32 was programmed using the Arduino IDE, while Python 3 was used on the Raspberry Pi to connect the main processing tasks. OpenCV handled image capture and preprocessing, and TensorFlow/Keras was used to run the MobileNet model. MQTT managed real-time data communication, MySQL stored the sensor readings and classification results, and the web dashboard presented the monitoring data to the user. Table 1 summarises the hardware and software used in the system and the role of each component.

Table 1. Hardware and software components used in the monitoring system.

Component	Function
Raspberry Pi 4	Edge computing and image processing
ESP32	Sensor data acquisition
DHT22 sensor	Temperature and humidity measurement
USB camera	Image acquisition
Wi-Fi module	Wireless communication
Power supply	System power source
Arduino IDE	ESP32 programming
Python 3	Image processing and system integration
TensorFlow/Keras	CNN MobileNet inference
OpenCV	Image preprocessing
MQTT broker	Real-time communication
MySQL	Data storage
Web dashboard	Real-time monitoring interface

Research Procedure

The research procedure began by defining what the system needed to monitor. Temperature and humidity were selected as the environmental variables, while the existing MobileNet model provided the three behavioural categories used in the study. These requirements were then used to

https://doi.org/10.58797/cser.040105

design a system that could collect environmental data and analyse quail images within the same monitoring process.

The hardware was assembled in the next stage. The DHT22 sensor was connected to the ESP32 to measure temperature and humidity inside the cage. The ESP32 sent these readings through Wi-Fi to the Raspberry Pi 4 using MQTT. A USB camera was also connected to the Raspberry Pi and positioned to capture quail activity in the cage.

The software was then set up to bring the two types of data together. The Raspberry Pi received the environmental readings from the ESP32 and the images from the camera. Sensor readings were stored in MySQL, while the captured images were preprocessed before being passed to the MobileNet model for behavioural classification. The environmental readings and classification results were then presented together on the web dashboard.

After the hardware and software had been integrated, the complete system was tested for five days. The evaluation compared DHT22 readings with reference instruments, checked MQTT data transmission and image classification, examined whether the dashboard displayed the required information, and measured the time between image capture and alert delivery. The test also examined whether these parts could operate together as one monitoring system.

Each device had a specific role in this workflow. The DHT22 provided the temperature and humidity measurements used in the experiment, while the ESP32 collected and published these readings through MQTT. The Raspberry Pi handled image preprocessing and MobileNet inference locally, so the captured images did not need to be sent to a cloud service for classification. The dashboard brought the sensor readings, behavioural classification, historical records, and alerts into one interface. In this way, the completed system linked environmental sensing, embedded programming, network communication, image classification, and data visualisation in a single monitoring process.

System Design

The monitoring system was organised into three functional layers: perception, edge computing, and application. Together, these layers describe how environmental readings and camera images move from the quail cage to local processing and finally to the monitoring interface. Figure 1 shows this architecture.

The perception layer collects data directly from the cage. The DHT22 sensor records temperature and humidity, while the USB camera captures images of quail activity. These two inputs provide the environmental and behavioural data used by the system.

The edge computing layer handles data acquisition and local image processing. The ESP32 reads the DHT22 measurements and publishes them through MQTT. The Raspberry Pi 4 receives these readings and processes the images captured by the camera. Image preprocessing and MobileNet inference are performed locally on the Raspberry Pi, which classifies each image into one of the three operational categories: Normal, Stress, or Aggressive.

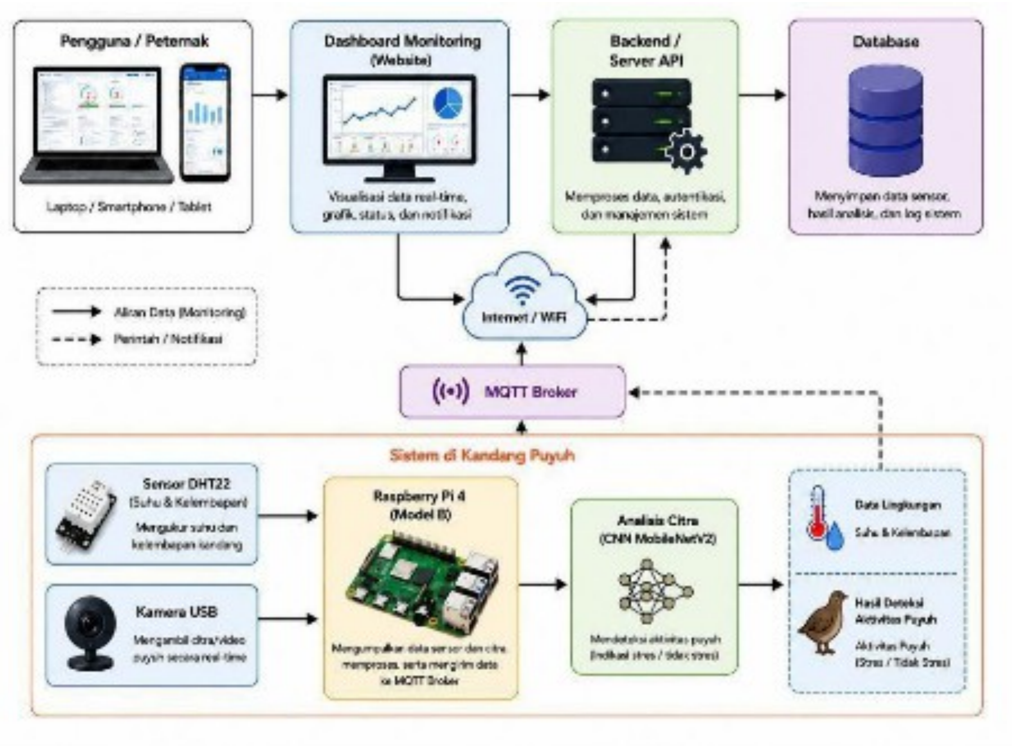

Figure 1. Block diagram of the proposed monitoring system.

The application layer brings the system outputs together for monitoring. The MQTT broker manages data exchange, MySQL stores the environmental readings and classification results, and the web dashboard displays the current values, behavioural category, and historical records. The notification function also generates an alert when the system identifies a configured environmental or behavioural condition.

Figure 2 presents the hardware connections used in the monitoring device. Figure 3 shows how data move through the complete system, from sensing and image capture to processing, storage, dashboard display, and user notification.

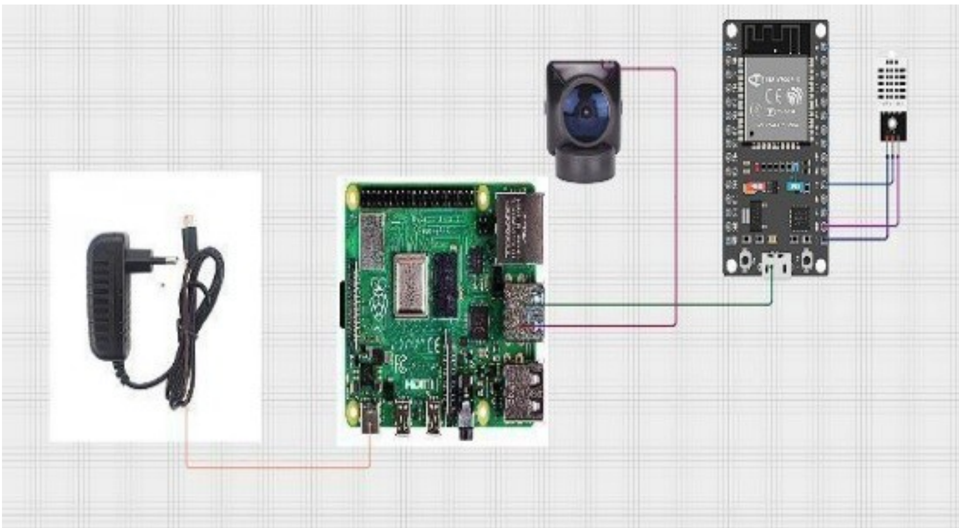

Figure 2. Hardware circuit of the monitoring device.

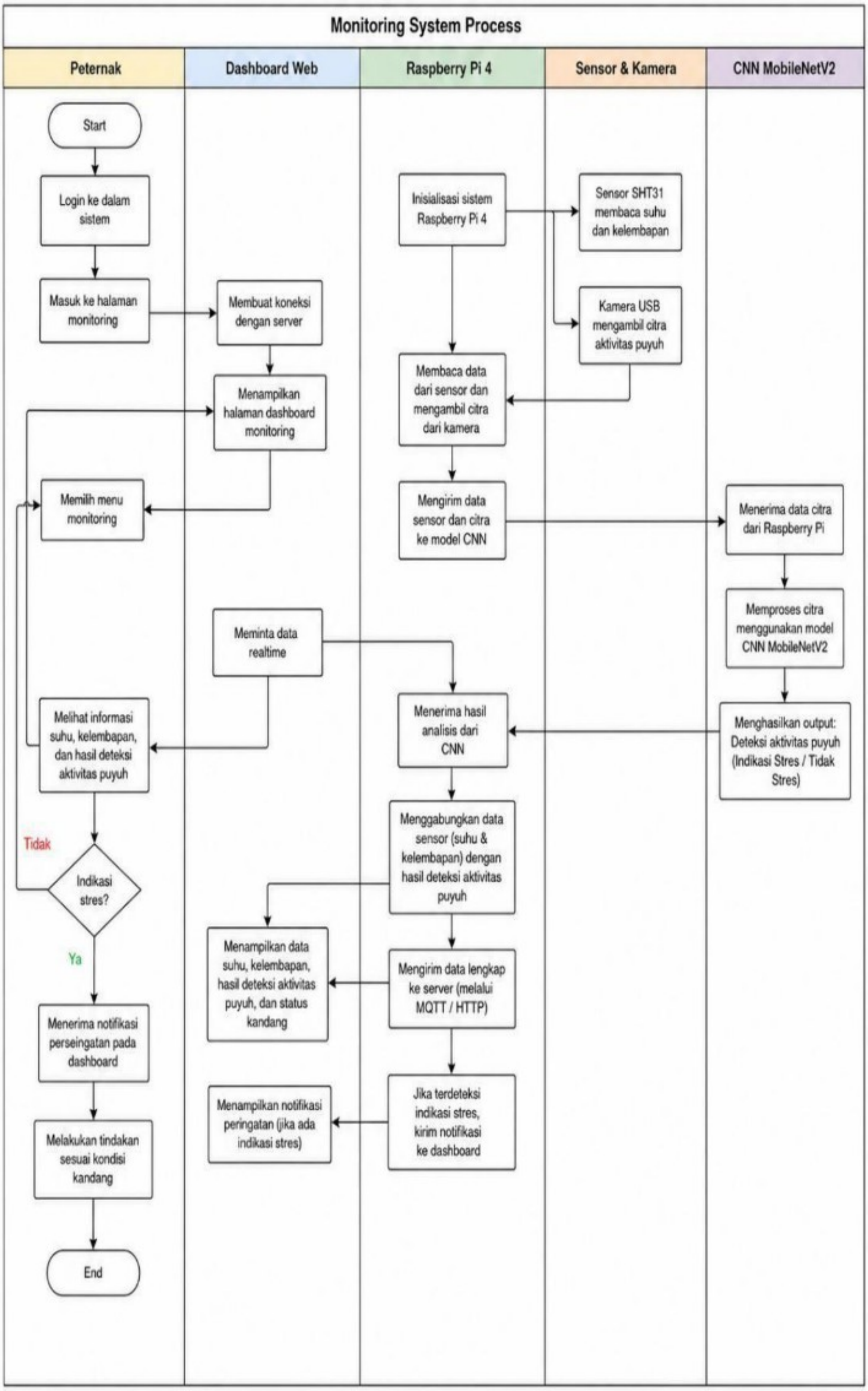

Figure 3. System workflow diagram.

Software Design

The software was divided between the ESP32 and the Raspberry Pi according to the task performed by each device. The ESP32 program, developed in the Arduino IDE, reads temperature and humidity from the DHT22 sensor and publishes the measurements through MQTT.

On the Raspberry Pi, a Python program receives the environmental data and handles the image-processing tasks. OpenCV is used to capture and preprocess images from the USB camera, after which the MobileNet model classifies each image into one of the three behavioural categories. The environmental readings and classification results are then stored in the MySQL database.

The web dashboard retrieves these records and presents the current temperature and humidity, behavioural classification, historical data, and system alerts in one interface. This allows the environmental readings and model output to be viewed together rather than through separate monitoring tools. Users can therefore check the cage remotely over an internet connection. Figure 4 shows the dashboard interface.

Figure 4. Web dashboard showing real-time temperature, humidity, and behavioural status.

Image Dataset, Preprocessing, and CNN MobileNet

The completed model-development dataset contained 1,200 labelled quail images distributed across three operational categories: Normal, Stress, and Aggressive. Images were resized to 224 × 224 pixels and normalised to the range 0–1 before being supplied to the MobileNet architecture. The trained model was converted for TensorFlow Lite inference on the Raspberry Pi, allowing classification to run locally at the edge.

The category names describe the image labels used for model training and should be interpreted cautiously. The completed experiment did not include physiological stress measurements that could independently validate the Stress category as a clinical state. In addition, the retained model-development documentation does not preserve class-wise image counts, the identity or number of annotators, an inter-rater agreement statistic, the exact training–validation ratio, complete training hyperparameters, or sequence-level metadata needed to test whether adjacent images from one behavioural sequence entered different subsets. These details cannot be reconstructed retrospectively without new data and are therefore reported as a reproducibility limitation rather than inferred after study completion.

System Testing and Evaluation

Testing was carried out to verify the performance of the monitoring platform. The system was evaluated in five areas:

1. temperature and humidity measurement using the DHT22 sensor;
2. MQTT data transmission between the ESP32 and the Raspberry Pi;
3. image classification using the MobileNet model;
4. data display and notification functions on the web dashboard; and
5. operation of the complete system during the five-day observation period.

To check the DHT22 measurements, sensor readings were compared with a reference thermometer and a reference hygrometer under the same conditions. The percentage difference between each sensor reading and its corresponding reference value was calculated using Equation (1).

$$Error\ (\%) = |Sensor\ Reading - Reference\ Reading|\ /\ Reference\ Reading \times 100\% \quad (1)$$

For the CNN evaluation, the records from the completed experiment included an overall validation accuracy of 91.3% and confidence scores for individual test scenarios. These measures describe different aspects of model performance. Validation accuracy shows the proportion of correctly classified images in the validation data, whereas the confidence score is the model output for a single prediction and should not be interpreted as overall accuracy (Guo et al., 2017). The original confusion matrix and class-level prediction results were not retained. Therefore, precision, recall, F1-score, and class-wise performance could not be recalculated from the available records (Sokolova & Lapalme, 2009). Only the performance measures available from the original experiment are reported in this study.

RESULTS AND DISCUSSION

This section reports how the monitoring system performed after the hardware and software components were brought together. The results are presented for the assembled device, the DHT22 measurements, image classification, dashboard functions, and the operation of the complete system during the five-day test.

System Implementation

The completed system combined environmental monitoring and image-based behaviour classification on the same platform. The DHT22 sensor collected temperature and humidity readings from the cage, and the ESP32 sent these data through MQTT to the Raspberry Pi 4. At the same time, a USB camera positioned above the cage captured images of quail activity.

The Raspberry Pi processed the camera images locally using the MobileNet model and assigned each image to one of three operational categories: Normal, Stress, or Aggressive. This allowed the sensor readings and behavioural classifications to be produced within the same monitoring process rather than as separate outputs.

Figure 5 shows the assembled device used during testing. During the five-day observation period, the sensor, camera, Raspberry Pi, MQTT communication, database, and dashboard were operated together as one system. Image classification was performed locally on the Raspberry Pi without sending the images to an external cloud service.

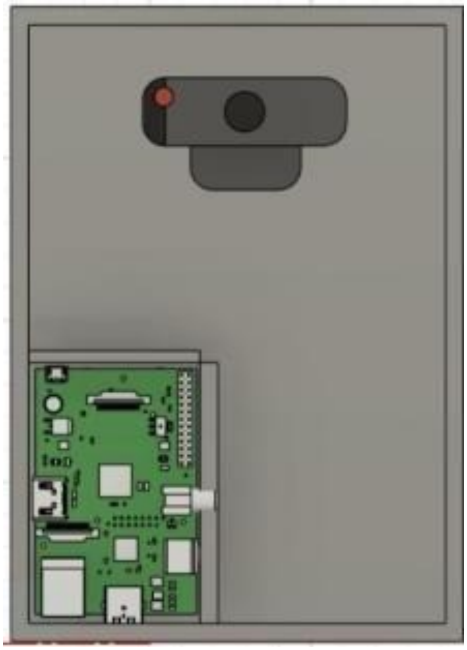

Figure 5. Implementation of the proposed monitoring device

Sensor Accuracy Testing

To check the DHT22 readings, the measured temperature and humidity were compared with values from a reference thermometer and hygrometer under the same conditions. The difference between the sensor and reference values was calculated as a percentage using Equation (1). Table 2 shows the results for temperature.

Across the five measurements, the temperature error ranged from 0.34% to 0.40%, with an average of 0.36%. The DHT22 readings were therefore very close to those of the reference thermometer at the conditions tested. However, these five comparisons only show the agreement

https://doi.org/10.58797/cser.040105

observed during this experiment and do not represent a full calibration of the sensor across its complete operating range. Table 3 presents the humidity results.

Table 2. Temperature accuracy test results.

Test	Sensor Temperature (°C)	Reference Thermometer (°C)	Error (%)
1	28.1	28.0	0.36
2	29.4	29.5	0.34
3	27.6	27.5	0.36
4	30.2	30.1	0.4
5	28.8	28.7	0.35

Table 3. Humidity accuracy test results.

Test	Sensor Humidity (%RH)	Reference Hygrometer (%RH)	Error (%)
1	67.5	67.2	0.45
2	69.8	70.1	0.43
3	66.4	66.2	0.3
4	71.3	71.0	0.42
5	68.2	68.0	0.29

For humidity, the error ranged from 0.29% to 0.45% across the five comparisons, with an average of 0.38%. Together with the temperature results, these measurements show that the DHT22 produced values close to the reference instruments during the test period. This supports its use in the prototype under the conditions examined here. However, the comparison covered only a limited range of temperature and humidity, so a wider calibration test would be needed before making a general claim about sensor accuracy.

Camera and CNN MobileNet Testing

The USB camera and CNN MobileNet pipeline were tested for image acquisition and real-time classification. Five functional scenarios were recorded, as shown in Table 4.

Table 4. Camera and CNN MobileNet testing results

Test	Scenario	Status	Result
1	Camera connected to Raspberry Pi	Detected	The USB camera was recognised by the Raspberry Pi operating system without additional drivers.
2	Still image acquisition	Success	Captured images were displayed clearly on the application interface.
3	Real-time video capture	Success	The video stream ran without interruption in the recorded test scenario.
4	CNN classification of Normal behaviour	Success	The system classified the test image as “Normal” with a confidence score of 100.0%.
5	CNN classification of Stress behaviour	Success	The system classified the test image as “Stress” with a confidence score of 100.0%.

The functional tests show that the image pipeline could acquire images and return classifications in the selected scenarios. The two 100.0% confidence values should not be interpreted as 100% accuracy or as evidence that the model is generally reliable. They are confidence outputs for two clear scenario images. Neural-network confidence can be poorly calibrated and does not necessarily represent the probability that a prediction is correct (Guo et al., 2017). The broader model result available from the completed experiment is the aggregate validation accuracy of 91.3%.

A fuller evaluation would normally report a confusion matrix and class-wise precision, recall, and F1-score because aggregate accuracy can hide differences between classes and between types of error (Sokolova & Lapalme, 2009). Those outputs are not available from the completed experiment. This is particularly important here because a Stress-to-Normal error could delay an alert, while a Normal-to-Stress error could generate an unnecessary alert. Recent poultry computer-vision studies also show that performance can differ markedly by behaviour and dataset, and that lighting, occlusion, overlapping postures, background variation, limited metadata, and class ambiguity can reduce generalisability (Bhujel et al., 2025; Merenda et al., 2024; Paneru et al., 2026; Yang, Bist, Paneru, Liu, et al., 2024). These factors provide plausible sources of error for future evaluation rather than explanations that can be confirmed from the present aggregate records.

Dashboard Monitoring Testing

The web dashboard was tested to determine whether it displayed sensor data and classification results in real time. Five scenarios were tested, and Table 5 presents the results.

Table 5. Dashboard monitoring testing results.

Test	Component Tested	Status	Result
1	Website access	Success	The dashboard was accessed through a web browser on a laptop and a smartphone.
2	Real-time graph update	Success	Temperature and humidity graphs updated automatically when new sensor data arrived.
3	Behavioural status display	Success	CNN classification results were displayed on the dashboard.
4	Notification alert	Success	An on-screen alert appeared when the configured Stress category was detected.
5	Historical data log	Success	Sensor readings and classification history were stored in the database and could be retrieved.

Table 5 shows that the dashboard functions included in the test were completed successfully. The dashboard combined environmental measurements and image-classification outputs, refreshed graphs when new data arrived, displayed behavioural categories, generated configured alerts, and retained historical records.

This integration is the main system-level contribution. MQTT provides a lightweight communication layer that can support low-latency livestock monitoring architectures (Ko & Lee, 2025), while the local edge-inference design reduces dependence on continuous cloud image processing. The present test demonstrates that the components worked together in this prototype; it does not establish long-term uptime or reliability beyond the five-day evaluation.

Integrated Environmental and Behavioural Monitoring

The integrated analysis placed DHT22 measurements and MobileNet classifications in the same record. Table 6 summarises the five observation days. The purpose of this comparison is to examine co-occurrence between environmental conditions and model-labelled behaviour, not to infer a causal relationship from five daily observations.

Table 6. Integrated environmental and behavioural monitoring results.

Day	Avg. Temp (°C) / Humidity (%RH)	Behavioural Category	CNN / System Observation
1	28.1 / 67.5	Normal	Quail activity was classified as Normal with 98.6% confidence.
2	28.6 / 68.0	Normal	Environmental readings remained within the range observed during the test, and no Stress category was produced.
3	29.3 / 69.4	Stress	The highest daily temperature and humidity in the five-day record coincided with increased jumping activity; the model assigned the Stress category with 100.0% confidence.
4	27.9 / 66.8	Normal	Temperature and humidity decreased relative to Day 3, and activity was classified as Normal.
5	28.5 / 68.5	Normal	System monitoring continued, with an average end-to-end notification latency of 4.7 seconds reported for the integrated test.

During the five-day test, daily average temperature ranged from 27.9 °C to 29.3 °C and humidity from 66.8% to 69.4%, with sensor sampling at one-minute intervals. Across the model-development dataset of 1,200 labelled images, the aggregate validation accuracy was 91.3%. On Day 3, the highest daily temperature and humidity values in the observed range coincided with increased jumping activity and a Stress classification. This observation illustrates why environmental and behavioural information can be useful when viewed together, but one co-occurring event does not establish that the environmental change caused the behaviour or that a validated stress threshold was crossed.

The cautious interpretation is consistent with poultry studies showing that ambient heat can be associated with changes in activity, dispersion, and other behaviours, while responses vary with housing conditions, bird age, heat intensity, and time of day (Duenk et al., 2024; Oso et al., 2025). Behaviour-monitoring research also shows the value of combining computer vision with welfare assessment, but emphasises the need for species- and context-specific validation (Campbell et al., 2024; Yang, Bist, Paneru, & Chai, 2024). For this prototype, the integrated dashboard therefore provides contextual evidence for an alert rather than a physiological diagnosis.

From a systems perspective, the 4.7-second average end-to-end latency shows that the completed pipeline could move from image capture to alert delivery within seconds during the test. Edge-AI studies in poultry similarly show that lightweight models can support local, real-time inference under constrained computing resources (Cakic et al., 2023; Tong et al., 2024). The present contribution is the combination of that local inference with concurrent microclimate sensing and a shared user interface.

Limitations and Model-Validation Needs

The findings need to be read within the conditions of the experiment. The complete system was observed for five days in one cage, and temperature and humidity varied within a relatively narrow range. The test therefore did not show how the system would perform during severe heat stress or under different farm conditions, seasons, cage designs, or flock sizes. The behavioural categories also were not checked against independent physiological measures of stress. For this reason, the categories produced by the model should be treated as behavioural classifications rather than confirmed physiological stress conditions.

There are also limits to what can be concluded from the CNN results. The two 100.0% values reported for individual scenarios are confidence scores for those particular images, not measures of overall model accuracy. In addition, the retained records do not contain enough detail to reconstruct class distribution, annotator agreement, complete training hyperparameters, or whether images from the same behavioural sequence were separated between training and validation data. Class-wise precision, recall, F1-score, and a confusion matrix are also unavailable. Taken together, these limits mean that the present results show that the system could operate under the conditions tested, but they are not sufficient to establish broader model validity or reliability across farm settings.

A stronger evaluation would need data from more cages, birds, and farm conditions, including a wider range of temperature and humidity. Behavioural labels should follow a clearly documented ethogram and labelling procedure, preferably with more than one annotator or an independent validation step. Training and validation data should also be separated at the behavioural-sequence level, and model performance should be reported for each class using precision, recall, F1-score, and a confusion matrix. Testing the trained model on new birds and housing conditions would provide a clearer indication of how well it performs outside the original dataset. These steps are particularly important in livestock computer vision, where well-annotated datasets collected across diverse conditions and accompanied by sufficient metadata are still limited (Bhujel et al., 2025).

Potential Educational and Interdisciplinary Applications

Although this study did not involve students or measure learning outcomes, the platform can serve as an authentic context for interdisciplinary STEAM learning. A single monitoring problem requires learners to connect environmental science and animal welfare with sensor measurement, calibration, embedded programming, MQTT communication, database handling, data visualisation, and AI-based image classification. IoT-based STEM ecosystems have been proposed specifically to support data-driven thinking, and work with authentic scientific datasets can help learners interpret variation, uncertainty, and evidence rather than only clean textbook data (Benita et al., 2021; Kjelvik & Schultheis, 2019). AIoT project-based learning also provides a model for linking physical sensors, digital data, and AI concepts within one design task (Cheng et al., 2025).

For example, a future learning activity could ask learners to formulate a question about the relationship between cage microclimate and quail activity, inspect or collect temperature and humidity records, compare model predictions with direct observations, identify possible false alerts or missed detections, and propose science-based husbandry responses. Such an activity would make the difference between measurement, evidence, model prediction, and decision making visible. It could also introduce the ethical question of how automated classifications should be used when animal welfare decisions are involved.

The platform could also be extended toward citizen science, particularly for science-based quail-care education. In a future participatory design, farmers, students, or community groups could collect standardised environmental observations, annotate selected behaviour images using a shared protocol, compare patterns across cages or locations, and contribute data to a common dataset. Citizen-science research shows that participation can connect learners with authentic scientific work and support reasoning with data-based claims (Aristeidou et al., 2023; Dvir & Tsybulsky, 2025). Community-based STEM research has likewise used real environmental monitoring to connect science and engineering practices with locally meaningful problems (Musavi et al., 2018).

This possibility should not be overstated. The present study is not a citizen-science project because citizens or learners did not participate in scientific knowledge production, and no educational outcomes were assessed. Moreover, classroom-based citizen science does not automatically improve every learning outcome; the design of the activity, the quality of participation, and explicit links to curriculum and reasoning matter (Williams et al., 2021). The educational and citizen-science uses proposed here are therefore testable directions for future research, not demonstrated effects of the current system.

CONCLUSION

This study developed an IoT and edge-AI platform that combines quail-cage temperature and humidity monitoring with image-based classification of three operational behavioural categories: Normal, Stress, and Aggressive. The DHT22 comparisons produced mean reported errors of 0.36% for temperature and 0.38% for humidity, the completed MobileNet experiment reported an aggregate validation accuracy of 91.3% on 1,200 labelled images, and the integrated pipeline produced an average notification latency of 4.7 seconds.

The main result is the technical feasibility of placing environmental sensing, local computer-vision inference, MQTT communication, database storage, dashboard visualisation, and alerting in one low-cost workflow under the tested conditions. The evidence does not support a claim of general field reliability or a physiological diagnosis of stress because the evaluation was limited to five days in one cage, the environmental range was narrow, and detailed class-wise model-evaluation records are unavailable.

Beyond farm monitoring, the platform may be useful as an authentic interdisciplinary learning environment in which learners connect environmental evidence, animal welfare, sensing, programming, data analysis, and AI. A future citizen-science extension could involve learners and farmers in standardised environmental observation and behaviour annotation for science-based quail-care education. These educational applications remain hypotheses for future empirical study and were not evaluated in the present research.

STATEMENTS AND DECLARATIONS

Competing Interests. The authors declare that they have no competing interests.

Author Contributions. All authors contributed to the development and completion of the study according to their respective roles in system design, hardware and software development, testing, data interpretation, and manuscript preparation. All authors reviewed and approved the final version of the manuscript.

Ethics Approval. The study involved environmental monitoring and camera-based observation of quails under the conditions described in the Method section. No human participants were involved.

Informed Consent to Participate. Not applicable.

Consent for Publication. Not applicable.

Data Availability. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Use of Artificial Intelligence Tools. Artificial intelligence was used in two distinct contexts in this study. As part of the research methodology, a Convolutional Neural Network based on the MobileNet architecture was used for image classification, as described in the Method section. During manuscript preparation, the authors used ChatGPT (OpenAI) to assist with English-language editing and grammar. All AI-assisted language edits were reviewed and revised by the authors, who take full responsibility for the final content of the manuscript.

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