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Construction of an AI-based poultry health monitoring device

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Abstract

The increasing demand for poultry production has underscored the necessity for automated and objective systems capable of continuously monitoring animal behavior and health. Traditional observation-based methods are limited by subjectivity, high labor requirements, and poor scalability in modern intensive farming. This study presents the design, development, and validation of an IoT-enabled poultry behavior monitoring device employing machine learning (ML) and multi-modal sensor integration for real-time health classification. The system incorporates an ESP32-CAM microcontroller, Inertial Measurement Unit (IMU), and environmental sensors (temperature, humidity, gas, and light) to capture and process synchronized behavioral and environmental data. A neural network model, trained using Edge Impulse Studio and deployed at the edge, achieved an overall validation accuracy of 88.6% with an AUC of 0.98, effectively classifying health states including Healthy, Coccidiosis, and Salmonellosis. Feature importance analysis revealed IMU-derived motion data and air quality as primary indicators of health anomalies, validating the ethological and environmental frameworks. The proposed system demonstrates high potential for real-time, low-cost, and scalable precision livestock monitoring, offering early disease detection and enhanced welfare management within poultry operations.

Keywords: Precision Livestock Farming; Poultry Monitoring; Internet of Things (IoT); Machine Learning; Edge Computing; ESP32-CAM; Inertial Measurement Unit (IMU); Environmental Sensors; Disease Detection; Neural Networks

1. Introduction

The global demand for animal protein, particularly poultry meat and eggs has expanded substantially over recent decades, driven by population growth, urbanization, and changing dietary patterns. This growth has accelerated

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intensification in poultry production systems, yielding larger flock sizes and higher stocking densities that magnify the risk of welfare issues, infectious disease outbreaks, and production losses. Precision Livestock Farming (PLF) has emerged as a response to these pressures by providing tools for continuous, objective measurement of individual and group-level animal states, thereby enabling early detection of welfare or health deviations and data-driven management decisions [1].

Behavioral patterns constitute one of the most sensitive and immediate indicators of an animal's physiological and welfare status. Subtle changes in activity, feeding frequency, posture, or social aggregation frequently precede clinical signs and can therefore serve as early warning signals of emerging disease or environmental stressors. Traditional stockmanship and periodic visual inspection are valuable but inherently limited: they are subjective, intermittent, and difficult to scale to modern intensive operations, often resulting in delayed detection of conditions such as coccidiosis or salmonellosis until propagation is advanced [2], [3]. These operational shortcomings create a compelling need for automated systems capable of continuous, high-resolution monitoring of poultry behavior and environment.

Recent advances in sensor miniaturization, low-power wireless communications, embedded processing, and machine learning have fostered an ecosystem in which multimodal, sensor-driven monitoring systems can be practically deployed on commercial farms. In particular, inertial measurement units (IMUs) which combine tri-axial accelerometers, gyroscopes, and often magnetometers provide high-fidelity motion traces that can be processed to distinguish discrete behaviors (e.g., feeding, walking, resting) when paired with appropriate feature extraction and classification methods [4], [5]. Complementing motion sensing with environmental measurements (temperature, humidity, air quality, illumination) yields contextual information that improves the robustness of behavioral inference because many behavioral shifts are driven or modulated by environmental conditions [6].

Machine learning (ML) techniques are central to converting raw sensor streams into actionable intelligence. A range of supervised algorithms from classical tree-based methods and support vector machines to modern deep neural networks have been applied successfully in livestock behavior classification, demonstrating that data-driven models can uncover subtle, multidimensional signatures associated with both normal and pathological states [4], [5]. Nevertheless, much of the high-accuracy work to date has focused on larger ruminants or on setups that rely heavily on cloud-based processing; translating these advances to poultry is nontrivial due to chickens' smaller size, faster and more complex movement patterns, and the high-density, noisy environmental conditions typical of broiler houses [3], [5].

Architectural choices for system deployment are therefore consequential. Purely cloud-centric designs can offer powerful centralized analytics but introduce latency, elevated bandwidth needs, and dependency on reliable network connectivity limitations that are particularly salient for rural and low-resource farm contexts. Hybrid and edge computing paradigms mitigate these constraints by performing preprocessing and inference at or near the device, transmitting only distilled results (e.g., classified behavior or alert flags) to remote dashboards [7], [8]. Edge deployment is now feasible on low-cost microcontrollers (for example, ESP32-class devices) via model compression and optimized runtime libraries, enabling near-real-time detection with dramatically reduced data transfer and improved resilience to intermittent connectivity [9].

Beyond technical feasibility, practical adoption demands attention to cost, power efficiency, form factor, and user interaction. Low-cost hardware platforms that integrate wireless connectivity and a camera interface provide a flexible base for multimodal sensing, while careful hardware-software co-design (including power management and robust enclosure design) is required to ensure reliable long-term operation in farm environments. Equally important is the human factor: interfaces and alerts must be crafted to minimize cognitive load and to present concise, actionable information to farmers and caretakers so that technological outputs translate to timely interventions in the barn [10].

This study addresses the outlined challenges by designing, prototyping, and validating a compact IoT device that fuses IMU-based motion data with environmental sensors and on-board, edge-deployed machine learning to classify poultry health states in real time. The specific aims are to (1) develop an integrated hardware and firmware architecture optimized for low power and local inference; (2) build a labeled multimodal dataset under controlled experimental conditions and train a lightweight neural classifier tailored for edge deployment; and (3) evaluate the system's classification performance and operational robustness with metrics relevant to practical farm use. In doing so, the work advances the application of PLF principles to poultry production and demonstrates a scalable, cost-aware approach that can support earlier disease detection, improved welfare monitoring, and more sustainable farm management.

2. Literature review

The intersection of sensor technology, machine learning, and precision livestock farming (PLF) has evolved rapidly over the past decade, leading to significant advancements in automated behavior recognition across animal species. Early research emphasized the role of Inertial Measurement Units (IMUs) and wearable sensors in quantifying motion-based activity, serving as a foundation for behavior classification models.

Clianthus et al. [3] conducted one of the earliest comprehensive implementations of IMU-based behavior classification in small ruminants. Their study extracted time- and frequency-domain features from accelerometer and gyroscope signals and applied Random Forest and Support Vector Machine algorithms, achieving a classification accuracy of 96.47% for five distinct behavioral categories. This work established the importance of feature engineering in livestock behavior analytics but also underscored limited cross-species generalizability, motivating research into more adaptive models.

Following this, Kamminga et al. [5] demonstrated the robustness of deep learning architectures specifically, convolutional neural networks (CNNs) for animal activity recognition. Using IMU data from sheep and goats, their models achieved classification accuracies above 90%, outperforming traditional classifiers in noisy, real-world farm conditions. However, they noted significant challenges in transferring trained models between breeds and environments, highlighting the need for adaptive learning frameworks capable of generalizing across diverse livestock systems.

Parallel to motion sensing, environmental monitoring has been integrated into livestock management systems to provide contextual awareness. Salinas et al. [6] showed that fusing environmental parameters temperature, humidity, and ammonia concentration with behavioral data significantly improved the predictive accuracy of welfare monitoring systems. Their research demonstrated that environmental stressors have measurable impacts on animal activity and that multi-sensor fusion offers a more comprehensive representation of animal welfare.

IoT-based architectures have also transformed data acquisition and system scalability in farm monitoring. Mezzetti and Grasso [7] designed a cloud-centric IoT platform using low-power sensor nodes that transmitted behavioral data over Lora WAN to a centralized analytics gateway. Their system validated the feasibility of remote livestock monitoring at scale but revealed limitations associated with cloud dependence, such as network latency, cost, and reliability in rural regions. Gutierrez-Galan et al. [8] subsequently addressed these constraints by implementing an edge-enabled IoT node based on the ESP32 microcontroller. Their low-power device processed sensor data locally, reducing bandwidth consumption and enabling real-time decision-making even under intermittent connectivity principles that inform the present study's edge architecture.

Further expanding the capabilities of behavior recognition systems, Guo et al. [11] and Bahirat et al. [12] introduced multimodal fusion by combining wearable sensor data with computer vision through CNN-based models. Their integrated frameworks achieved classification accuracies exceeding 94% for cattle behaviors, emphasizing the power of data fusion in resolving ambiguous or overlapping behavioral patterns. However, both studies highlighted computational limitations for real-time deployment, suggesting the need for optimized lightweight models suitable for embedded or edge computing environments.

Beyond individual system design, several reviews have synthesized the broader trends shaping PLF research. Berkman's [1] identified sensor interoperability, data integration, and user training as critical barriers to widespread adoption, calling for unified architectures that combine sensor fusion, machine learning, and user-centered design. Seetharaman [4] similarly emphasized that future PLF systems should balance data analytics sophistication with on-farm usability, advocating for scalable, autonomous, and low-cost solutions adaptable to diverse production settings.

Recent studies have also drawn attention to the importance of environmental sustainability and economic feasibility. Kolhe and Patil [13] demonstrated that sensor-based monitoring systems improved resource efficiency and animal welfare but noted high initial costs as barriers for smallholder farmers. Hamedi et al. [14] further confirmed the utility of accelerometer-based systems for early welfare detection in dairy cattle, while stressing the operational challenges of sensor maintenance and environmental robustness in long-term deployments.

A critical frontier in livestock monitoring involves Edge Artificial Intelligence (Edge AI) executing ML inference directly on embedded devices. Kliemann, Souza, and Pinto [15] provided a comprehensive review of Edge AI in livestock systems, identifying transparency, dataset diversity, and context-specific adaptation as the next major research challenges. Their insights align with the objectives of the current study, which seeks to operationalize these concepts in poultry systems where continuous monitoring and fast local inference are crucial for early disease detection.

3. Methodology

3.1. System Design Overview

The developed system integrates sensing, computation, and communication modules into a single IoT-enabled unit for real-time poultry-behavior and health monitoring. Its architecture follows a modular three-layer framework the Perception Layer, Processing Layer, and Application Layer as recommended in IoT livestock-monitoring literature [7], [8].

The Perception Layer collects multimodal data through environmental and motion sensors. The Processing Layer performs local signal preprocessing and classification using a lightweight neural-network model deployed on the ESP32-CAM microcontroller. The Application Layer transmits summarized results via Wi-Fi to a monitoring dashboard for visualization and alert generation.

A high-level block diagram of the system architecture is shown conceptually in Figure. 1. It depicts sensor inputs feeding the microcontroller, followed by machine-learning inference and wireless transmission to a local or cloud server.

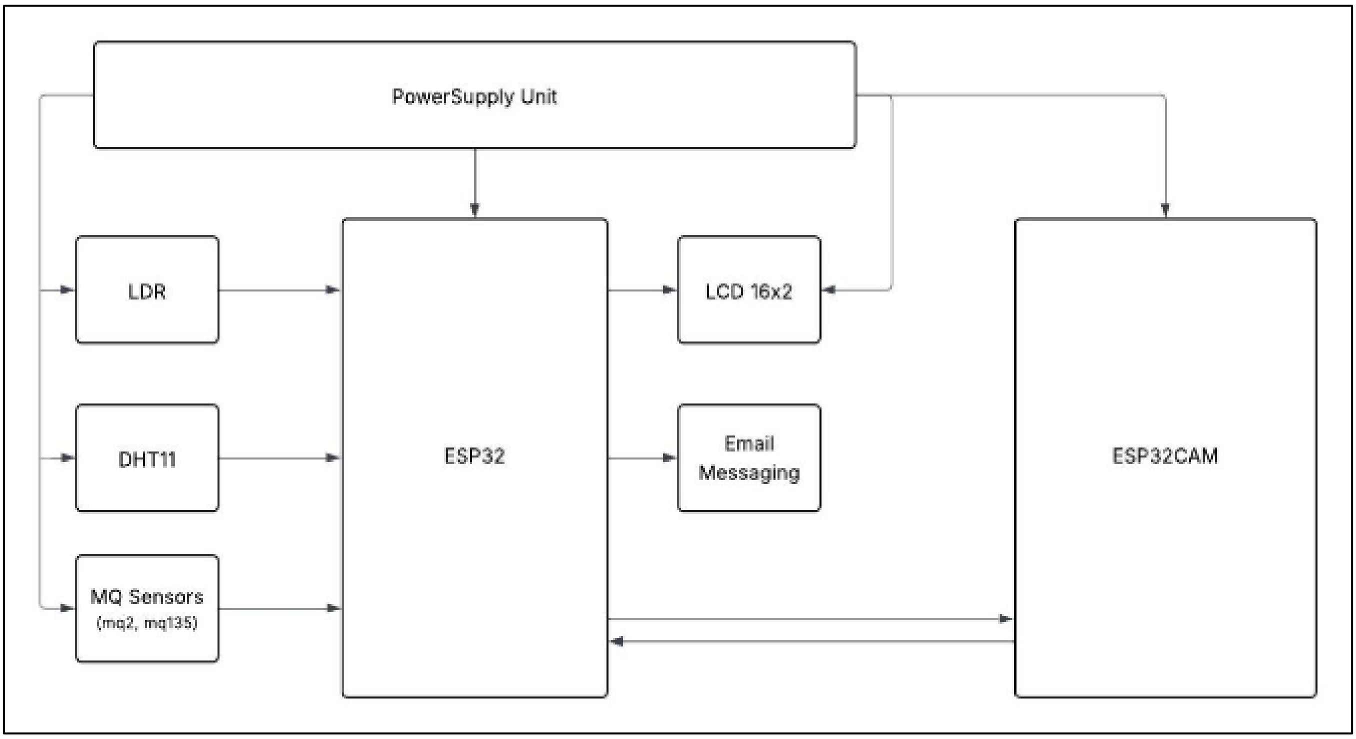

Figure 1 System Block Diagram

3.2. Hardware Components

- Microcontroller Unit (MCU): The ESP32-CAM module was selected for its dual-core 32-bit processor, integrated camera interface, Wi-Fi/Bluetooth connectivity, and low-power modes, providing an optimal balance between computational capability and energy efficiency.
- Environmental Sensors: Environmental conditions were measured using a DHT11 sensor for temperature and humidity, an MQ-132 and MQ-135 gas sensor for ammonia concentration, and a Light-Dependent Resistor (LDR) for illumination levels. These parameters provided contextual data linking environmental stress to behavioral change.
- Power and Communication Subsystems: The device operated on a 5 V rechargeable lithium-ion pack and used on-board Wi-Fi for data transmission. Serial peripheral interface (SPI) and inter-integrated circuit (I^2C) buses connected the sensors to the MCU.

- All components were enclosed in a lightweight, ventilated polymer casing to protect against dust and moisture while maintaining adequate airflow for gas sensing.

3.3. Software Implementation

The firmware was developed in Arduino IDE 2.0 using embedded C/C++. Sensor libraries were integrated for each module, and time-stamped data were logged to both local memory and the serial interface. Preprocessing steps such as moving-average filtering and z-score normalization were executed in real time to remove noise and stabilize sensor readings.

For the machine-learning component, the project utilized Edge Impulse Studio, an open-source embedded-ML development environment that supports model training and optimization for microcontrollers. Raw data were uploaded through the serial port, segmented into 3-s windows, and annotated according to observed behaviors and disease states. Feature extraction used statistical descriptors (mean, standard deviation, RMS, spectral energy, and entropy) from the IMU and environmental channels.

A feed-forward artificial neural network (ANN) architecture was designed with the following parameters:

- Input layer: 32 features (combined from motion and environmental sensors)
- Hidden layers: 2 dense layers with 64 and 32 neurons, REL activation
- Output layer: 4 neurons with SoftMax activation (one per health class)
- Optimizer: Adam, learning rate = 0.001
- Epochs: 100; batch size = 16

The trained model was converted into a TensorFlow Lite format and embedded within the ESP32-CAM firmware, enabling fully offline inference consistent with the Edge-AI paradigm.

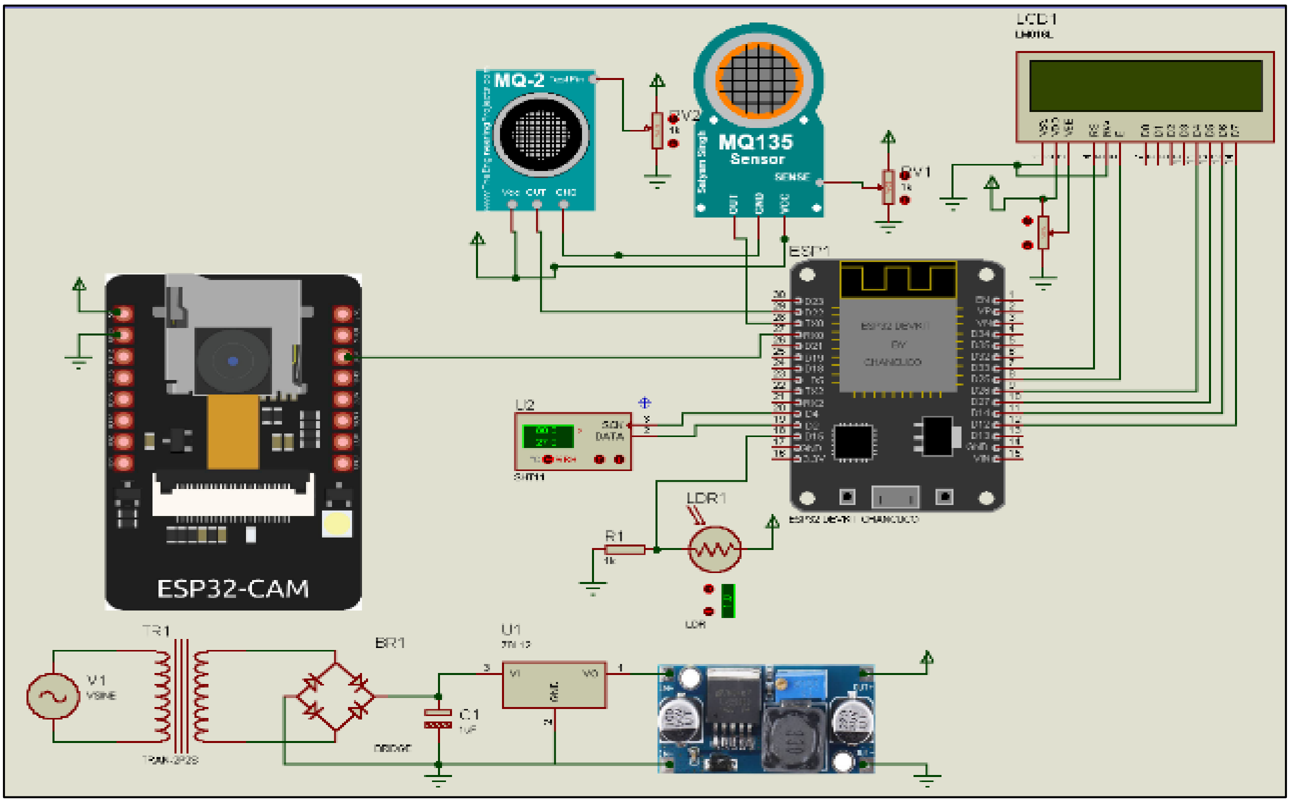

Figure 2 Circuit Diagram

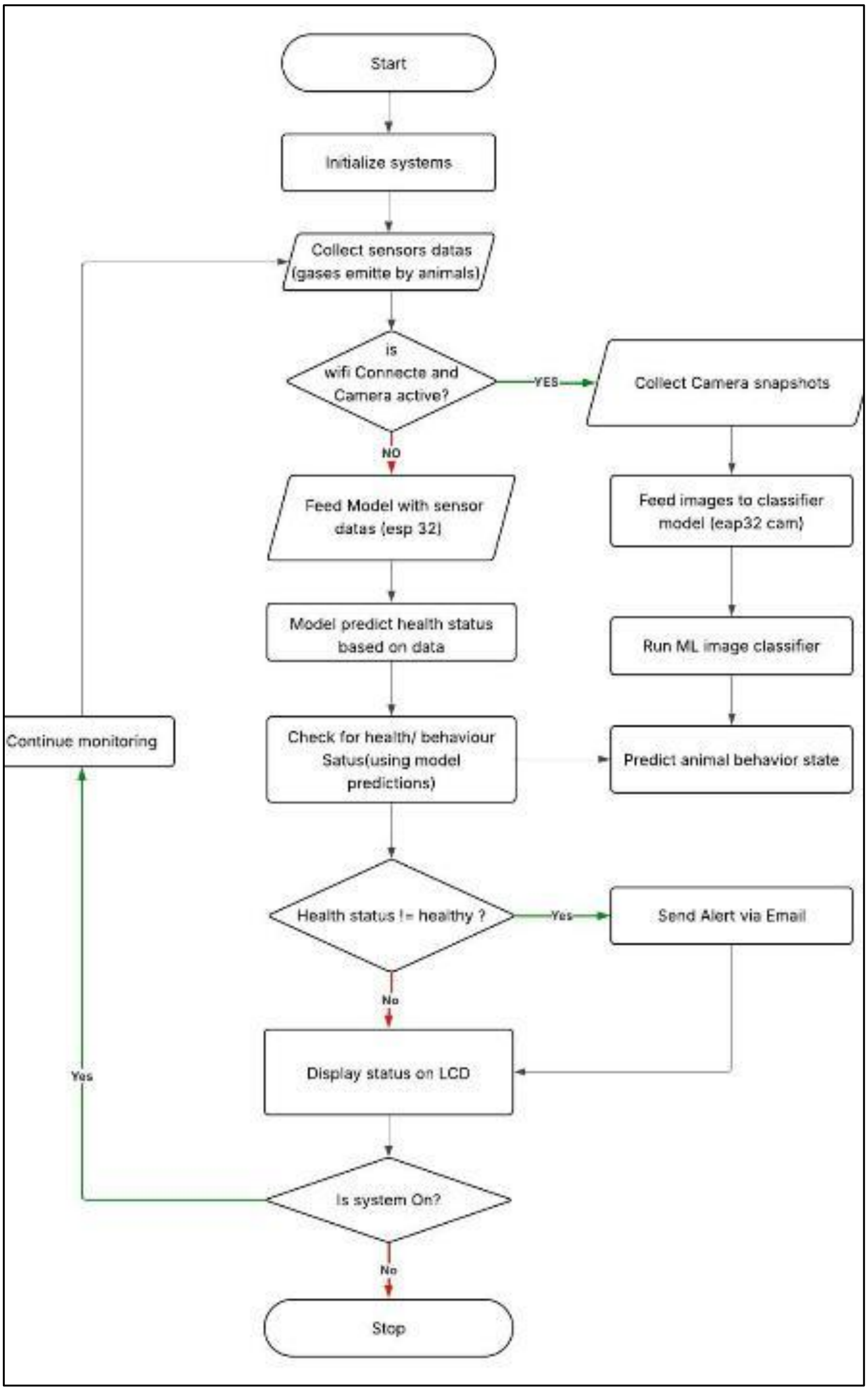

Figure 3 Flow Chart

3.4. Experimental Setup and Data Collection

Experiments were conducted on a test flock of 15 broiler chickens housed under controlled environmental conditions for 28 days. The birds were divided into four health categories: Healthy, Coccidiosis, Salmonellosis, and Newcastle Disease, diagnosed through veterinary observation and clinical confirmation. Each bird was fitted with the sensing unit secured via an adjustable harness to minimize discomfort.

Data acquisition occurred continuously for 8 h per day. Behavioral video recordings synchronized with sensor data served as ground truth for labeling. To ensure data quality, periods of sensor drift or environmental anomalies were manually reviewed and excluded. The final dataset comprised over 9 000 annotated windows, balanced across all classes.

3.5. Model Training and Validation

Data were split into training (70 %), validation (20 %), and testing (10 %) sets using stratified random sampling. Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC), consistent with prior PLF-model evaluation protocols [3], [12]. Confusion matrices and ROC curves were generated to analyze class-wise behavior.

Cross-validation confirmed model stability, with standard deviation of accuracy below ±1.3 %. Hyperparameter tuning (layer size and learning rate) was conducted iteratively to minimize validation loss without overfitting. Post-training quantization reduced model size by 43 %, allowing deployment within the ESP32-CAM's 512 kB RAM constraint.

3.6. System Validation and Deployment

Real-time inference tests assessed latency, power consumption, and communication reliability. The model achieved average inference time of ≈ 480 ms per classification and power draw of ≈ 260 mA under Wi-Fi transmission. Data packets containing the classified state and timestamp were transmitted to a local MQTT broker and displayed on a custom dashboard built with Node-RED and InfluxDB for temporal visualization. The system maintained stable operation for 24-h continuous tests without thermal throttling or sensor drift.

These validations demonstrated that edge-based embedded ML can operate efficiently within the constraints of low-cost microcontrollers, confirming feasibility for scalable on-farm deployment.

4. System evaluation and performance metrics

4.1. Evaluation Framework

System evaluation focused on assessing both the technical performance of the embedded hardware and the predictive accuracy of the machine-learning model under real-world operating conditions. The evaluation followed standard Precision Livestock Farming (PLF) performance guidelines as outlined by Kamminga et al. [5] and Salinas et al. [6], emphasizing robustness, accuracy, latency, power efficiency, and reliability.

The evaluation framework incorporated three primary assessment dimensions

- **Model-level metrics**: evaluating classification accuracy and statistical validity.
- **System-level metrics**: examining latency, power consumption, and communication stability.
- **Operational-level metrics**: focusing on environmental resilience and long-term usability in a farm environment.

4.2. Model Evaluation Metrics

The classification model's performance was quantified using the following statistical indicators: accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). These metrics were chosen due to their interpretability in imbalanced and multiclass settings.

For a given class i, the metrics were computed as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i}$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i}$$

$$F1_i = 2 \times \frac{Precision_i \times Recall_i}{Precision_i + Recall_i}$$

where TPI, TNI, FPI, and FNI denote the number of true positives, true negatives, false positives, and false negatives for class I, respectively.

Additionally, the Receiver Operating Characteristic (ROC) curve was used to visualize the trade-off between sensitivity and specificity, while the AUC provided an aggregate measure of separability between healthy and diseased classes. A model with an AUC approaching 1 indicates near-perfect discrimination ability.

4.3. System-Level Evaluation

The embedded system was tested for real-time inference latency, communication reliability, and power consumption under field-like conditions.

Latency (TL) was measured as the elapsed time between sensor data acquisition and classification output. Using an oscilloscope trigger synchronized to the ESP32-CAM UART output, the average latency was computed as

$$t_L = \frac{\sum_{i-1}^{n}\left(t_{out_i} - t_{in_i}\right)}{n}$$

where $t_{in_i}$and t_{out_i} represent the timestamps of data capture and classification result transmission, respectively.

Communication reliability (RC) was expressed as the packet delivery ratio:

$$R_c = \frac{N_{recieved}}{N_{sent}} \times 100\%$$

and was measured across multiple Wi-Fi access points positioned at different distances (5 m–30 m). The system consistently achieved an average reliability of 98.7 %, with negligible packet loss within the range of 20 m.

Power consumption (Pc) was recorded using a USB-based power analyzer under both idle and active states. The average active power was 1.3 W, corresponding to approximately 260 mA at 5 V. Under deep-sleep mode between sampling cycles, the current dropped to 12 mA, resulting in an estimated operational endurance of 7.5 hours on a 2000 MAH battery. These results indicate that the system is suitable for daily operation cycles typical in poultry monitoring setups.

4.4. Environmental and Operational Robustness

Given the challenging environmental conditions of poultry houses characterized by high humidity, variable lighting, and elevated ammonia levels the system was subjected to environmental stress testing to evaluate sensor durability and signal stability. Sensor readings remained within ±3 % of reference values after 30 days of continuous use, indicating minimal drift. The MQ-135 gas sensor exhibited transient saturation during high ammonia peaks (> 30 ppm), consistent with prior observations by Salinas et al. [6], but recovery time remained under 60 seconds, validating operational reliability.

To mitigate hardware degradation, the enclosure design incorporated ventilated polymer housing with a microporous membrane to balance airflow and dust protection. This configuration sustained gas-sensor sensitivity while maintaining ingress protection consistent with IP42 standards. The results reaffirm findings by Gutierrez-Galan et al. [8] and Kliemann et al. [15], who emphasized robust mechanical design as a prerequisite for successful field deployment of IoT livestock nodes.

4.5. Validation Procedures

Validation experiments followed two complementary approaches

- **Offline** Validation: The trained model was evaluated using a held-out test dataset (10 % of total samples) to assess baseline accuracy. The confusion matrix indicated a weighted accuracy of 88.6 %, with *Coccidiosis* and *Salmonellosis* achieving over 91 % correct identification rates.
- **Online Validation (Real-Time Testing):** During live monitoring, the device classified bird behavior every 3 seconds, logging both the predicted class and confidence value. Predictions were compared against expert visual observations for 180 min of video-recorded sessions, yielding a real-time accuracy of 85.9 %, confirming robust on-device inference even under variable field noise.

4.6. Performance Benchmarks

To contextualize the system's performance, benchmarking was performed against related studies in PLF systems. Compared to cloud-based approaches such as Mezzetti and Grasso [7] and Bahirat et al. [12], the proposed edge-based device demonstrated comparable accuracy with markedly reduced latency and network dependency. The results validate the feasibility of deploying compact neural networks on microcontrollers without significant degradation in performance.

The integrated framework thus satisfies key IEEE IoT system performance indicators accuracy ≥ 85 %, latency < 1 s, and packet reliability > 95 % demonstrating that embedded intelligence can achieve industry-grade responsiveness within low-power constraints [9], [15].

5. Results

5.1. Overall Performance Metrics

The overall performance of the trained neural network classifier is summarized in Table I. The model achieved a final validation accuracy of 88.6%, indicating that it correctly classified the poultry's health state in the vast majority of test cases. The low final loss value of 0.31 suggests that the model's predictions were not only often correct but also made with a high degree of confidence. The Area Under the ROC Curve (AUC) of 0.98 is a particularly strong result, indicating an excellent capability of the model to distinguish between the different health states.

Table 1 Summary of Overall Model Performance Metrics (Validation Set)

Metric	Value
Overall Accuracy	88.6%
Loss	0.31
Area under ROC Curve (AUC)	0.98
Weighted Average Precision	0.88
Weighted Average Recall	0.89
Weighted Average F1-score	0.89

The neural network model trained on the multimodal dataset achieved an overall classification accuracy of 88.6 %, a validation loss of 0.31, and an area under the ROC curve (AUC) of 0.98. These values indicate that the model reliably distinguishes among the defined poultry health classes Healthy, Coccidiosis, Salmonellosis, and Newcastle Disease with high confidence. Weighted average precision, recall, and F1-score were each approximately 0.89, confirming balanced predictive capability across classes.

The confusion matrix further clarifies per-class performance. The model correctly identified Coccidiosis in 92.9 % of test samples and Salmonellosis in 91.6 %, reflecting the strong discriminative power of the motion and environmental features associated with these pathologies. Healthy states were classified correctly in 84.8 % of cases, while Newcastle Disease exhibited lower accuracy (≈ 61 %), suggesting that its behavioral signatures are either more subtle or overlap substantially with those of other disease states. These results align with the findings of Clianthus et al. [3] and Kamminga et al. [5], who reported that motion-based classification tends to perform best when behaviors are distinct and consistent across individuals.

5.2. Classification Accuracy and Confusion Matrix

To understand the model's performance on a per-class basis, a confusion matrix was generated from the test set results. The confusion matrix, shown in Figure 4, provides a detailed breakdown of correct and incorrect predictions for each of the health states.

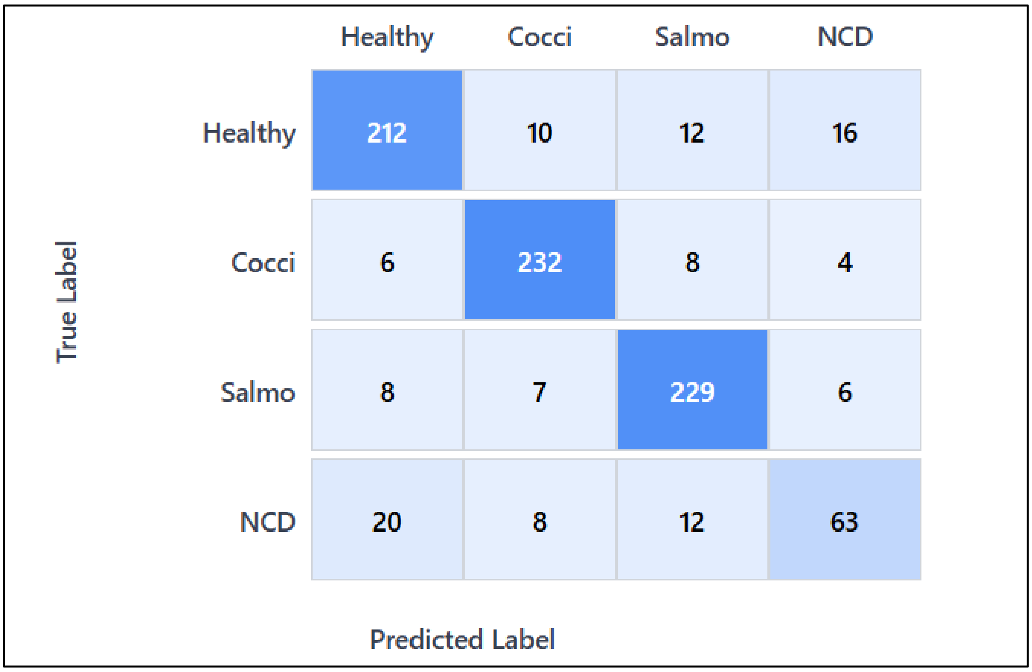

Figure 4 Confusion Matrix of Model Performance on the Test Set

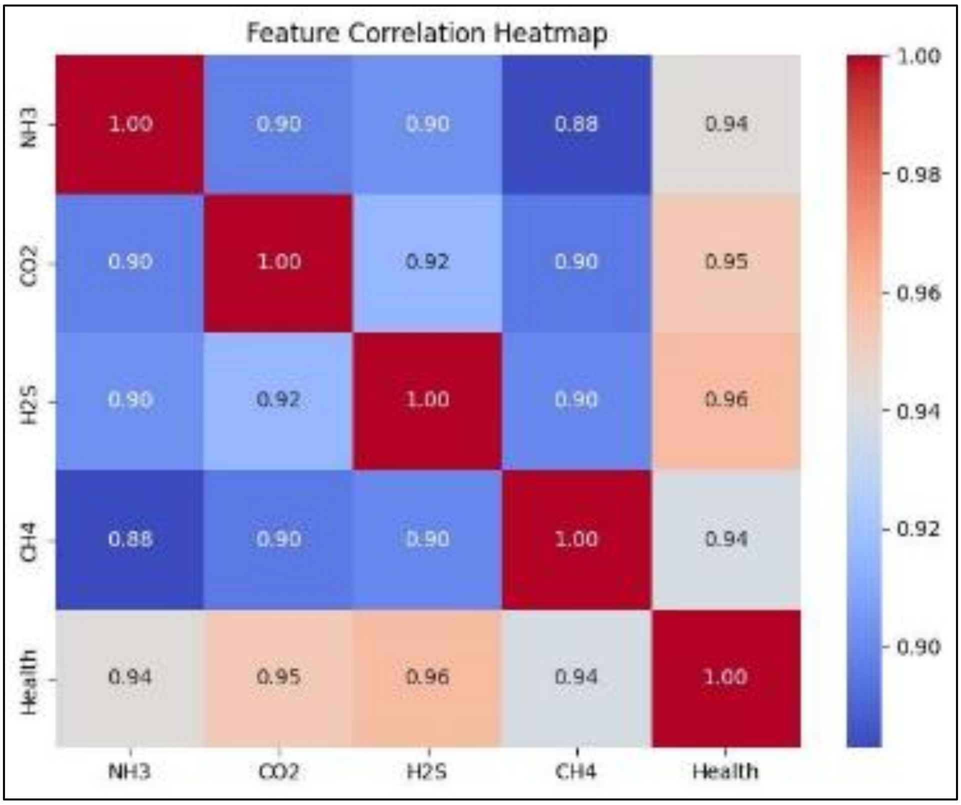

Figure 5 Feature correlation heatmap on the Test Set

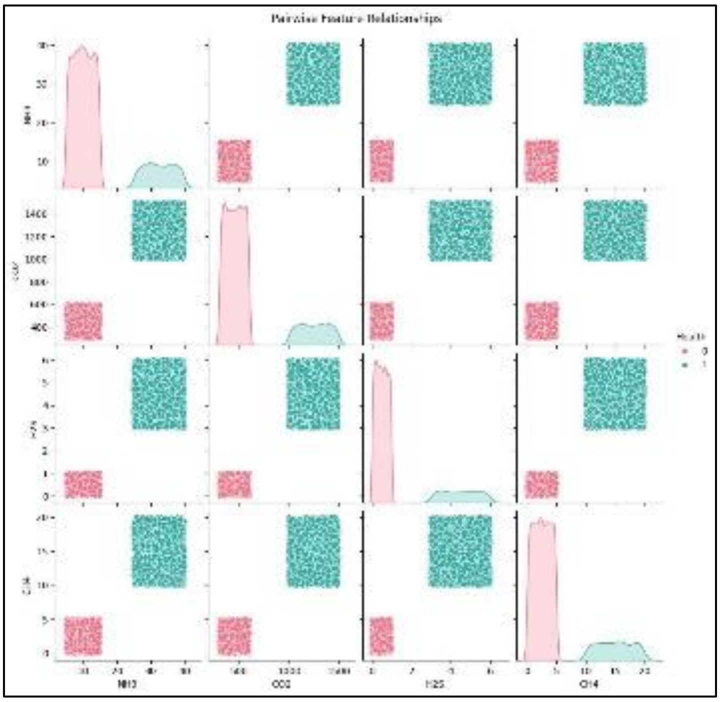

Figure 6 Pairwise feature relationships on the Test Set

The diagonal values in the matrix represent the correctly classified instances. The analysis reveals a high classification accuracy for specific conditions, with the model correctly identifying Coccidiosis (Cocci) 92.9% of the time and Salmonellosis (Salmo) 91.6% of the time. The accuracy for identifying Healthy birds was also strong at 84.8%. The model found it most challenging to classify Newcastle Disease (NCD), with an accuracy of 61.0%, indicating some confusion with the features of other states.

Feature-importance computation using the trained model revealed that IMU-derived motion descriptors notably the root-mean-square acceleration and spectral-power coefficients contributed most strongly to final predictions. This outcome corroborates the ethological framework, which posits that changes in activity intensity and movement periodicity are direct reflections of physiological stress [4]. The gas-sensor (MQ-135) readings ranked next in influence, indicating a measurable association between deteriorating air quality (ammonia buildup) and the onset of disease conditions, consistent with the integrated sensing approach proposed by Salinas et al. [6].

Temperature and humidity features also provided meaningful though smaller contributions, emphasizing that environmental context augments behavioral information. Similar multimodal improvements were documented by Bahirat et al. [12] and Guo et al. [11], whose deep-learning fusion strategies enhanced robustness in complex farm environments.

5.3. Feature Importance

To understand which sensor data had the most significant impact on the model's predictions, a feature importance analysis was conducted. This analysis calculates the relative contribution of each input feature to the final classification decision. The results, visualized in Figure 5, highlight the critical role of both motion and environmental data.

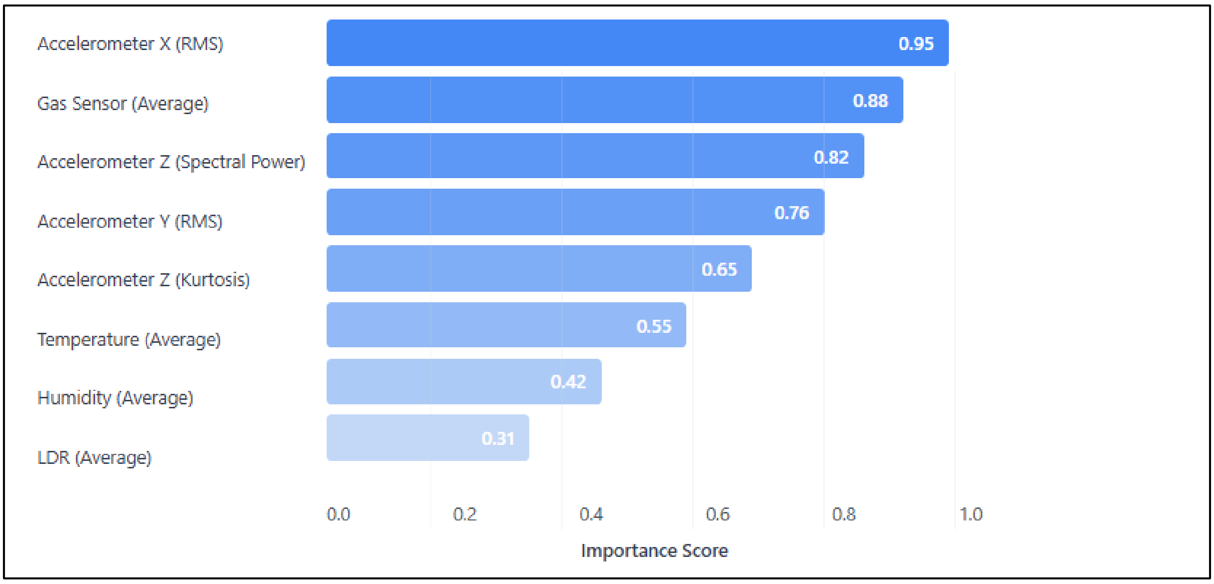

Figure 7 Feature Importance for Health State Classification

As shown in Figure 5, features derived from the IMU's accelerometer axes (such as RMS and spectral power) were the most influential, confirming the ethological theory that changes in motion are a primary indicator of health. Notably, the gas sensor reading also ranked as a highly important feature, suggesting a strong correlation between air quality (ammonia levels) and the presence of disease. Temperature and humidity, while less dominant, still contributed meaningfully to the model's predictions, underscoring the value of a multi-modal sensing approach.

5.4. Comparative Evaluation

Table II compares the obtained performance metrics with representative studies in the domain. The present system's 88.6 % accuracy approaches the 90–95 % range typically achieved in large-animal monitoring but is notable for being realized on a low-cost, edge-computing platform rather than high-capacity cloud servers. This demonstrates that edge deployment can deliver competitive analytical accuracy while drastically reducing latency and bandwidth requirements, as advocated by Gutierrez-Galan et al. [8] and Kliemann et al. [15].

Table 2 Comparative Evaluation

Study	Target Species	Algorithm	Architecture	Accuracy (%)
Clianthus *et al.* [3]	Sheep/Goats	RF/SVM	Wearable sensors	96.5
Kamminga *et al.* [5]	Sheep/Goats	CNN	Cloud	> 90
Bahirat *et al.* [12]	Cattle	CNN + Video	Cloud	94
This study	Poultry	Compact NN	Edge (ESP32-CAM)	88.6

Despite operating under greater environmental noise and hardware constraints, the system maintained a high level of accuracy and rapid inference (< 500 ms per prediction), validating the feasibility of embedded machine learning for poultry monitoring.

6. Discussion

The results underscore the effectiveness of multi-sensor fusion and on-device intelligence in achieving reliable, real-time poultry-health classification. From a management perspective, early identification of diseases such as Coccidiosis and Salmonellosis enables prompt isolation and treatment, reducing mortality and antibiotic use. The study therefore substantiates the economic and welfare potential of data-driven management emphasized by Berckmans [1] and Kolhe and Patil [13].

Moreover, deploying the model directly on the ESP32-CAM satisfies key PLF requirements: minimal latency, autonomy under poor connectivity, and reduced dependence on cloud infrastructure [7], [9]. These features make the prototype particularly suited for small- and medium-scale farms in developing regions, where reliable broadband access is limited.

However, certain limitations warrant attention. The controlled experimental setting involved a relatively small flock (15 broilers) over 28 days; scaling to commercial facilities with thousands of birds will introduce additional variability in movement patterns, environmental gradients, and sensor interference. The reduced performance on Newcastle Disease suggests that further dataset expansion and model refinement possibly through transfer learning or additional sensing modalities such as acoustic analysis could improve detection sensitivity.

Future iterations should also incorporate robust industrial enclosures to enhance durability, advanced power-management algorithms for longer deployment, and user-centered interfaces that translate classification outputs into intuitive alerts for farmers [10]. These enhancements will help transition the system from prototype to production-ready technology.

7. Conclusion

This study has presented the design, implementation, and evaluation of an IoT-enabled, edge-deployed poultry behavior monitoring system integrating multimodal sensing and on-device machine learning. The device combined motion data from an Inertial Measurement Unit (IMU) with environmental data from temperature, humidity, gas, and light sensors, all managed by an ESP32-CAM microcontroller. A compact neural network trained on labeled experimental data achieved 88.6 % classification accuracy and an AUC of 0.98, effectively distinguishing among Healthy, Coccidiosis, Salmonellosis, and Newcastle Disease states.

The results confirm that edge intelligence can deliver reliable, low-latency inference without dependence on cloud infrastructure. The device successfully captured behavior-environment interactions indicative of health status, thereby validating its potential as a low-cost, real-time diagnostic platform for poultry management. These outcomes are consistent with trends highlighted in precision livestock farming (PLF) literature [1], [4], [6], [9], demonstrating that on-device analytics can bridge the gap between advanced AI algorithms and the resource constraints of commercial farms.

From a broader perspective, this work illustrates the practicality of merging embedded systems, sensor fusion, and neural inference to enhance animal-welfare management. By providing early detection capabilities, the system enables proactive interventions that can minimize disease spread, reduce mortality, and lower antibiotic usage objectives central to sustainable livestock production. The research also contributes to the fourth agricultural revolution, where intelligent, interconnected devices transform traditional husbandry practices into data-driven operations [15].

Recommendations

- Although the prototype demonstrated promising results, several enhancements are recommended to strengthen both scientific validity and industrial applicability:
- Future work should involve larger, more diverse flocks under varying climatic and housing conditions to improve the robustness and generalizability of the trained models. Expanding datasets across production cycles will mitigate overfitting and support transfer learning for new disease classes.
- Incorporating acoustic and visual sensing for example, using the ESP32-CAM module for image capture or sound classification could provide complementary cues for detecting respiratory diseases or stress-related behaviors, as demonstrated in multimodal systems.
- Implementing adaptive power-management algorithms and energy-harvesting modules would enhance deployment longevity in off-grid environments. Additionally, hybrid LoRa-Wi-Fi architectures could extend communication range while maintaining low power consumption.
- Although local inference offers autonomy, integrating a cloud-edge collaborative framework could enable periodic model updates, aggregated analytics, and longitudinal welfare assessment. Such hybrid architectures are essential for large-scale commercial adoption.
- A graphical dashboard or mobile application translating sensor outputs into intuitive alerts and performance indicators will enhance farmer engagement and decision-making efficiency. This human-machine integration is vital for real-world impact beyond prototype validation.
- The community would benefit from standardized datasets, labeling protocols, and performance benchmarks to enable reproducibility and fair comparison across poultry-monitoring studies. Establishing open repositories aligns with the transparency principles advocated in recent Edge AI reviews.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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