RESEARCH ARTICLE

Embedded Electronic IoT System for Poultry Health Monitoring and AI-Powered Disease Detection from Feces

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Abstract

Poultry farming plays a vital role in global food production, requiring efficient management to ensure productivity and animal welfare. Traditional methods, largely based on manual monitoring, are often inefficient, error-prone, and costly. With the rise of Internet of Things (IoT) technologies, intelligent systems now enable remote monitoring and management of environmental conditions, farm operations, and disease prevention. Platforms such as ThingSpeak allow for real-time data collection, processing, and visualization, offering a cost-effective solution for poultry farm management. By integrating sensors to measure temperature, humidity, air quality, and feeding, and by leveraging ThingSpeak's analytical tools, farms can automatically adjust conditions and support proactive decision-making. This not only reduces operational costs but also improves efficiency, resource management, and animal health monitoring. The growing demand for poultry products has pressured farms to increase production, which heightens the risk of disease outbreaks and significant economic losses. Traditional disease detection methods, which depend on manual inspections by skilled professionals, are labor-intensive and delay timely intervention. To address these challenges, an IoT-based poultry disease detection and classification system is proposed. This system employs sensors for continuous health monitoring and artificial intelligence algorithms such as YOLOV7 and MobileNetV3 to analyze data. YOLOV7 segments regions of interest from automatically captured fecal images, while MobileNetV3 classifies them into four states: healthy, coccidiosis, salmonella, and Newcastle disease. Trained on Zenodo database samples, these models achieve high accuracy, providing farmers and veterinarians with an effective tool for proactive disease management and sustainable poultry farming.

Keywords: ESP32, YOLOV7 , MobileNetV3, IoT, intelligent poultry system, disease detection.

1 Introduction

The growing demand for poultry meat, due to its protein richness, low energy intake, and low cholesterol content, has led to a significant expansion

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in poultry production. In West Africa, particularly in Senegal, this sector has experienced rapid growth over the past few decades, responding to increased demand for broiler chicken, which has resulted in a notable rise in imports. However, maintaining high poultry production depends on various factors, such as environmental conditions, disease management, breeding practices, and effective resource administration. Effective management of poultry health and welfare is therefore crucial to prevent infectious diseases, improve productivity, and ensure the health of broilers. Nevertheless, traditional farming methods face significant challenges, including high labor costs and inefficient management of resources such as feed, water, and electricity. In response to these challenges, it is essential to adopt innovative solutions, such as the concept of "smart farms," to optimize management and productivity in poultry farming while minimizing errors and improving the living conditions of the birds.

Good management of poultry welfare can not only improve their overall health and living conditions but also reduce the spread of diseases and minimize economic losses. Early detection and classification of poultry diseases from chicken fecal images are essential for maintaining flock health and ensuring product quality. This enables timely interventions and the implementation of measures to control outbreaks and protect animals and consumers.

In this context, the integration of the Internet of Things (IoT) and deep learning (DL) emerges as a promising technology for intelligent poultry farming. These advanced technologies enable real-time monitoring of farming conditions, precise data analysis, and optimal decision-making to improve resource management and productivity in poultry operations. The IoT offers innovative technological solutions that can simplify operations for workers and poultry farm owners. These technologies allow for real-time monitoring of farms via the cloud, as well as remote control of environmental conditions, thus fostering more effective and responsive farm management. Meanwhile, deep learning can revolutionize the management and optimization of poultry farming. By analyzing images and videos of animals, deep learning systems can detect signs of disease, monitor growth, and assess environmental conditions with increased accuracy. This technology also enables the prediction of nutritional needs and the detection of behavioral anomalies, contributing to improved poultry welfare and maximized productivity.

In this work, we develop a low-cost and efficient remote management system for poultry farms, combining connected sensor technologies and artificial intelligence (AI). This system allows for real-time monitoring of environmental conditions such as ammonia (NH_3) levels, temperature, and humidity, as well as the health status of the poultry through an intelligent video surveillance device. The poultry disease detection system employs advanced object detection algorithms using YOLOV7 for region segmentation and pre-trained image classification algorithms using MobileNetV3 to classify images into four health states: healthy, coccidiosis, salmonella, and Newcastle disease. The sensors are connected to an ESP32 development board and use a Wi-Fi connection to transmit data to the ThingSpeak platform, enabling optimized remote management via a mobile application or online platform. The main contributions of this paper are summarized as follows:

- Designing an intelligent poultry monitoring system capable of identifying and classifying chicken diseases through fecal image analysis of chickens.
- Predicting four health states of poultry: healthy, coccidiosis, salmonella, and Newcastle disease via various deep learning techniques.
- Detecting and classifying the pathological state of poultry by classifying sick and healthy chickens from a poultry farm using fecal image analysis.
- Presenting a comprehensive experimental study of the work conducted and providing details on the various significant results obtained.

The article is organized as follows: Section 2 examines relevant prior studies related to our research. Basic concepts regarding IoT, ESP32, YOLO V7, MobileNetV3 , and the dataset are discussed in Section 3. Section 4 presents the methodology of the system. Section 5 provides details on the infrastructure of the proposed poultry farm system, while Section 6 describes the intelligent poultry health monitoring system. The experimental results are discussed in Section 7. Finally, Section 8 presents the conclusions of the paper and directions for future work.

2 Related works

Intelligent systems based on the Internet of Things (IoT) are revolutionizing poultry farming by providing optimized management of environmental conditions and improving animal welfare. These systems, through the real-time collection and analysis of essential data such as temperature, humidity, and gas levels, enable automatic regulation of conditions to ensure an ideal environment. The integration of renewable energy sources like solar energy and nano-hydropower, along with the use of edge computing solutions with devices like the Raspberry Pi, makes power supply and data processing more sustainable and cost-effective. The automation of tasks such as feeding and watering, combined with the ability to manage equipment remotely via mobile applications, reduces operational costs while increasing efficiency. Advanced alert systems, coupled with the application of artificial intelligence to monitor poultry health, allow for early detection of problems, thereby improving animal welfare and optimizing production. Due to their flexibility and scalability, these solutions are suitable for various types and sizes of farms, transforming poultry management into a more proactive and sustainable approach. Recent research has focused on the development of intelligent systems for poultry farming using the Internet of Things (IoT). One notable work proposes in [1] an IoT-based system that integrates renewable energy sources, such as solar energy and nano-hydropower, for power supply. This system collects diverse data via sensors, including temperature, humidity, toxic gas levels, and soil moisture. The collected data is stored in a central database, allowing for in-depth analysis and automatic regulation of environmental conditions to maintain optimal poultry health. Furthermore, the system offers remote control functionalities for equipment, doors, and bins via mobile devices and online platforms, thus facilitating remote management with an internet connection.

In [2], a proposal is made for an intelligent automated management system for poultry farming using the Internet of Things (IoT). This program manages feeding and watering of the poultry using sensors installed in the containers. It also includes an alarm that triggers in case of failure of essential components or dihydrogen monoxide. The lighting in the farm is regulated by a specific sensor. This system also enables automatic feeding of birds, continuous supply of dihydrogen monoxide, and egg collection.

In article [3], a weather monitoring system for poultry farming using the Internet of Things (IoT) is proposed. The DHT11 device is used to measure temperature and humidity in the proposed system. The collected data is transmitted to a cloud server, where it is stored in a database and continuously compared to defined thresholds. In the event of prolonged exceedance of these thresholds, the system sends an alert to the user's smartphone and triggers a sound signal via a buzzer. The system's validation was successfully completed, confirming its ability to send alerts to smartphones and activate the buzzer.

To address challenges related to behavior detection and health assessment of poultry, article [4] proposes an intelligent monitoring system for hens using IoT sensors. This system is designed to detect and monitor the behavior of poultry in farming operations, providing valuable data to industry stakeholders for management and individual animal health assessment. The proposed system includes several steps: data preprocessing, feature extraction, feature selection, and behavior detection of poultry using various classification algorithms. An optimized synthetic minority oversampling technique (SMOTE) is applied via an artificial hummingbird algorithm (AHA) to address the issue of data imbalance. Experimental results indicate that the optimized SMOTE, with an accuracy of 97%, outperforms other algorithms in managing data imbalances. Additionally, for accurate prediction of poultry behaviors, the Random Forest (RF) algorithm stands out with an accuracy of 98%, surpassing other machine learning algorithms.

In [5], an intelligent method has been developed to detect and classify hens based on their vocalization. This approach utilizes Fisher's Discriminant Analysis (FDA) combined with signal detection to differentiate healthy hens from sick ones. In [6], the authors developed an IoT platform that allows for real-time analysis of each hen's egg production, facilitating the replacement of hens whose production falls below a predetermined threshold to achieve overall yield goals. The health, cleanliness, and growth of the hens have been monitored using this platform [7]. Among the issues affecting poultry welfare, lameness is a major factor [8]. Early detection of lameness allows farmers and veterinarians to take preventive measures to improve poultry welfare.

Work [9] presents an intelligent system based on the Internet of Things (IoT) for monitoring and controlling environmental conditions in poultry farms. The system monitors essential parameters such as temperature, humidity, and air quality in a chicken coop to ensure an optimal environment for the poultry, reduce mortality rates, and improve production. The ESP32 microcontroller, equipped with built-in Wi-Fi capabilities, is used in conjunction with several sensors:

a DHT11 temperature and humidity sensor, a PIR motion detector, and an MQ135 gas detector. A buzzer is also included to alert the farmer in case of intrusion, and the Wi-Fi unit sends notifications to the farmer. The system also regulates the brightness of a lamp inside the coop to adjust the temperature. This prototype, tested in a small coop, demonstrated its effectiveness and achieved the set objectives.

The proposed research project in [10] aims to improve hen health and reduce mortality rates in farms in Brunei by automating the monitoring and maintenance of environmental conditions such as temperature, humidity, air quality, and feeding of the poultry. By using Internet of Things (IoT) and Wireless Sensor Network (WSN) technologies, a prototype has been developed to monitor these parameters and compare them to predefined thresholds. When the measured values exceed the established thresholds, the system automatically triggers corrective actions, thereby contributing to the reduction of mortality rates. Additionally, the system sends automatic alerts to the user via SMS, email, and WhatsApp. A web interface has also been established to enable real-time monitoring and display of environmental parameters.

The project described in [11] focuses on raising healthy laying hens, aiming to reduce mortality rates and improve the consistency of poultry products. To achieve these goals, the project utilizes wireless sensor network (WSN) and Internet of Things (IoT) technologies to effectively monitor and regulate critical parameters such as temperature, humidity, air quality, and feeding conditions. A model has been developed by integrating advancements in IoT and WSN, and critical thresholds have been tested against predefined limits. The system also provides scheduled notifications to users via SMS. Additionally, a web interface has been designed to filter and display these limits in real-time.

Article [12] offers an in-depth analysis of poultry health monitoring using an IoT-based platform that integrates artificial intelligence (AI) techniques. The studied system employs various IoT sensors, along with video and image processing, to monitor the health of poultry and birds. It also includes analysis based on the animals' vocalizations. The increasing accessibility of computational resources, IoT devices, and standard algorithms enhances the use of these modern technologies for continuous monitoring of large poultry farms with millions of birds, thereby improving overall productivity. Given that eggs and poultry are essential sources of protein, the adoption of advanced technological solutions for poultry management is highly recommended.

Article [13] proposes a cost-effective solution based on edge computing and the Internet of Things (IoT) for managing environmental conditions and disease control in poultry farms. The developed model measures temperature, humidity, greenhouse gases, and light intensity inside the chicken coop, transmitting this data to a local server built with a Raspberry Pi. Through edge computing, data processing occurs directly on this server, enabling intelligent information extraction for controlling various actuators on the farm. The use of low-cost computing devices, such as the Raspberry Pi, makes this system particularly affordable for farmers.

Article [14] presents "Feather Sense," an innovative IoT system specifically designed for poultry farming. This cloud-based solution uses the Telegram platform for data storage, real-time monitoring, and remote access. "Feather Sense" continuously monitors crucial environmental parameters such as temperature, humidity, and ammonia levels, providing detailed analyses. It offers farmers a user-friendly interface that facilitates remote monitoring and informed decision-making. Field trials in commercial poultry farms have shown that the system enhances productivity and poultry welfare. This approach promises to transform the poultry industry by offering an economic, scalable, and accessible solution for managing poultry farms.

Article [15] explores an effective method for organizing an intelligent poultry farming system based on IoT using specific IoT components. The proposed framework utilizes an Arduino Nano to interact with various sensors to monitor key environmental parameters such as temperature, odor concentration in the air, and light intensity. The collected data is then transferred to the cloud via an ESP32 Wi-Fi module. This system not only detects parameters but also actively manages them using automated methods. This framework is particularly useful for farmers applying regular cultivation practices, as it allows for remote management of the coop via mobile phones, thereby reducing the need for manual checks and improving overall farming efficiency.

In [16], Wang et al. used a deep learning technique to classify the condition of poultry droppings to facilitate disease detection within the flock. Zhuang et al. analyze the skeletal condition of infected broiler chickens in studies [17, 18]. In [19], Sibanda et al. aimed to identify outdoor laying hen subpopulations and describe their resource utilization habits, which can influence their performance and welfare. In three commercial farms, 3,125 Lohmann Brown hens were equipped with RFID bracelets and placed with their companions, totaling 40,000 hens per farm. The hens were monitored for their use of the aviary system, including feeding lines, nests, and the outdoor area. K-means and agglomerative analysis, optimized by the Calinski-Harabasz criterion, identified three distinct clusters. Significant individual variations were observed, with the largest differences noted at the upper feeder ($140 \pm 1.02\%$) and the outdoor area ($176 \pm 1.03\%$). Hens in cluster 1 spent the least time in the outdoor area and the most time at the upper-level feeder chain ($p < 0.05$). The results show an unequal load on resources and varied movement patterns within the aviary. Further analysis using classification models, such as support vector machines, artificial neural networks, and decision trees, is recommended to explore the impact of these factors on hen performance. In [20], Yuanzhou et al. developed the world's first manually annotated database for the classification of hen sex. This database contains 800 images of flocks taken on farms and 1,000 individual images obtained through an object detection network, along with information about the sex of the hens. Additionally, they designed a classifier using a deep neural network and cross-entropy, achieving an average accuracy of 96.85%. The results demonstrate that this automated method is effective for sexing hens in farm settings and provides a practical solution for estimating sex ratios.

The work presented in [21] describes a method to improve the feed conversion rate (FCR) in poultry farming through automated action plans. These plans, adjusted by computational intelligence combining deep learning and genetic algorithms, adapt over time based on previous results. A network infrastructure allows this method to be deployed in distributed chicken coops, with a supervisory system as the user interface. Tests based on real data show a 5% improvement over the performance of human specialists.

In [22], Nasiri et al. proposed a deep convolutional neural network to detect and track seven key points on the bodies of walking hens. These extracted key points were then fed into a long short-term memory (LSTM) model to classify the hens according to a six-level assessment method. This work proposes the first large-scale benchmark for estimating the pose of broiler chickens, including 9,412 images. Additionally, the dataset includes 400 videos (totaling 36,120 images) of chickens with different gait score levels. The developed LSTM model achieved an overall classification accuracy of 95%, with an average accuracy per class of 97.5%.

In [23], Li et al. developed a stretching behavior detector for broiler chickens based on a faster region-based convolutional neural network (faster R-CNN) to evaluate stretching behaviors under different stocking densities (27, 29, 33, and 39 kg/m^2) and examine their temporal and spatial distribution. The results showed that this detector had precision, recall, specificity, and accuracy greater than 86% for all densities and ages of the chickens. Broiler chickens stretched between 230 and 533 seconds per day, with a higher frequency observed at stocking densities of 29, 33, and 39 kg/m^2 at week 4, and at densities of 29 and 33 kg/m^2 at week 5. Stretching behaviors were less frequent a few hours after the lights were turned on and before they were turned off, occurring more in less frequented areas, such as along the fences. In conclusion, the detector demonstrated satisfactory performance for detecting stretching, revealing that this behavior varies according to stocking density and age of the chickens, as well as over time and space.

In [24], Küçüktopcu et al. developed a simple, accurate, rapid, and economical model to estimate ammonia (NH_3) concentration in poultry farms. Four models were tested: multilayer perceptron (MLP), adaptive neuro-fuzzy inference systems with grid partitioning (ANFIS-GP) and subtractive clustering (ANFIS-SC), and multiple linear regression (MLR). These models used easily accessible climatic variables and bedding properties. The performance of the models was evaluated using root mean square error (RMSE), mean relative percentage error (MRPE), and coefficient of determination (R^2). The ANFIS-SC model, using air temperature, relative humidity, and air velocity as inputs, showed the best performance with an RMSE of 1.130 ppm, an MRPE of 4.032%, and an R^2 of 0.858 for the validation dataset. The MLR model was the least accurate. The study concludes that the neurocomputing model (ANFIS-SC) is a reliable and effective alternative for estimating NH_3 concentration in poultry farms.

Article [25] presents an innovative method for determining the sex of day-old chicks using their vocalizations, addressing the challenges associated with the time-consuming manual identification of sex in poultry production. The proposed method employs sound technology to detect chick vocalizations and uses a double-threshold technique to automatically detect the endpoints of vocalizations, based on three parameters: short-term energy, short-term zero-crossing rate, and duration. For sex classification, three deep learning models—Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—were trained using audio features extracted from the vocalizations. The models were evaluated using a training set and a test set comprising vocalizations from different chicks to ensure robust performance. Results showed that the GRU model achieved the highest accuracy (76.15%) for sex detection, followed by LSTM (75.73%) and CNN (74.55%). The GRU model also obtained the highest recall (77.03%), while the LSTM model demonstrated the highest specificity (78.38%). Furthermore, for sex prediction based on vocalizations, the CNN exhibited the best performance with an average accuracy of 91.25%, compared to 87.08% for LSTM and 88.33% for GRU.

In [26], Fang et al. proposed a non-invasive method for analyzing the behavior of broiler chickens using pose estimation based on Deep Neural Networks (DNN) and pose classification via a Naive Bayesian Model (NBM). This approach allows the construction of a pose skeleton from feature points to track movements and identify behaviors such as standing, walking, running, feeding, resting, and feather preening, with accuracy ranging from 0.5135 to 0.9623 depending on the behavior. This automated method provides an efficient solution to replace human observation in poultry farming, allowing for rapid detection of behavioral anomalies and thereby improving health management and farm productivity.

In [27], Cuan et al. presented the Deep Poultry Vocalization Network (DPVN), an innovative method for early detection of Newcastle Disease (ND) in poultry by analyzing their vocalizations. The DPVN employs advanced techniques such as multi-window spectral subtraction and high-pass filtering to reduce noise and improve detection accuracy. The automatic vocalization detection method was evaluated with a recall of 95.11% and an accuracy of 96.54%. In terms of classification, the model achieved an accuracy of 98.50%, a recall of 96.60%, and an F1 score of 97.33%. Detection accuracy varied depending on the day after infection, with rates ranging from 82.15% on the first day to 98.50% on the fourth day. This promising approach allows for effective early disease detection, contributing to animal welfare and facilitating automated monitoring in poultry production.

In [28], Mahdavian et al. evaluated five acoustic features of bird calls to determine the health status of birds. Signals were collected from chickens raised in three groups: control group, group infected with bronchitis, and group infected with Newcastle Disease. Data analysis results showed that among the five studied acoustic features, wavelet entropy (WET) had the best performance and was capable of detecting bronchitis on the third day after inoculation with an accuracy of 83%, while the type II error in this test (incorrectly detecting a sick bird as healthy) was below 14% and 6% respectively on the third and fourth days. In the case of Newcastle Disease, although WET and Mel-frequency cepstral coefficients (MFCC) presented similar accuracy (80% and 78% respectively on the fourth day), the difference was that WET was more reliable for detecting healthy birds, while MFCC performed better in detecting infected birds.

In [29], You et al. developed an Artificial Neural Network (ANN) model capable of predicting the probability of daily laying events at a specific time of day. Using 706 recorded laying events from radio-frequency-equipped nests and 706 non-laying events, the study introduced a new anchor point as a temporal reference and created 26 features around this point for each event. The developed ANN model demonstrated exceptional performance with an area under the ROC curve of 0.9409. It enables prediction of laying events on the same day and provides informative probabilities for each individual breeder. In situations where the total egg production is known, this model can estimate the probability of laying for each bird and rank them to identify those most likely to have laid.

The literature identifies three main applications of IoT and machine learning in managing poultry health and welfare: first, monitoring the behavior and environment of poultry; second, disease analysis; and finally, control and intervention to optimize their welfare. The majority of studies on monitoring poultry behavior and environment focus on using IoT technologies to remotely monitor aspects such as feeding, resting, running, as well as environmental parameters like temperature and humidity. These systems enable automated and non-intrusive data collection, providing farmers with an instant and continuous view of the health and welfare of chickens. Research includes monitoring physiological responses (respiratory rate, cloacal temperature) [30–32], sex determination [20, 33], posture [22, 23], as well as real-time tracking of body weight [34, 35], laying events [36], and feed consumption [37, 38]. Additionally, several studies examine environmental parameters such as temperature, humidity, and pest presence, as well as detecting failures in poultry equipment.

Early identification of avian diseases to prevent their spread remains a major challenge in the poultry sector. However, numerous studies have introduced advanced technologies to improve rapid disease detection and diagnosis. Several studies [32, 39–41] aim to minimize reliance on manual observations and human decisions. The most frequently studied diseases include Newcastle Disease virus, avian influenza, capillary diseases, Salmonella, hock burn, and the prevalence of Listeria spp. Common methods for identifying sick poultry include analyzing feeding habits [38], observing movements and postures [26], checking weight [35], and analyzing sounds produced by poultry [32].

Effective management of poultry health relies on careful monitoring of environmental parameters such as temperature, humidity, ventilation, and lighting. Precise regulation of these factors is essential for maintaining optimal conditions in poultry houses, contributing to improved animal welfare, reduced energy consumption, and increased productivity. The use of advanced sensors allows for automatic control of ventilation, lighting, cooling, and heating systems. For instance, systems developed by [33, 42] demonstrate respective accuracies of 93.70% and 97.00% in regulating temperature and humidity. Other studies, such as those by [43], illustrate the integration of sensors to monitor various parameters such as water levels and harmful gas levels. In parallel, feeding optimization strategies aim to improve production efficiency while reducing costs, as demonstrated by the work of [44, 45]. Finally, low-complexity systems, like the one by [46], allow adjustment of poultry environments with an accuracy of 80.00%, offering an economical solution for controlling farming conditions.

Research in machine learning (ML) aims to develop computer programs capable of generating or improving knowledge from data. Traditional techniques require technical expertise to extract features from raw data, while deep learning automates this process, facilitating feature extraction without prior expertise. Deep learning architectures, such as convolutional neural networks, are particularly effective for image processing. ML models, whether supervised or unsupervised, use historical data to predict new outcomes and find increasing applications in poultry welfare management. They are used to monitor environmental parameters, assess thermal stress, track poultry behavior, and detect diseases, thereby improving the health and productivity of farms.

Deep learning (DL) is widely used to enhance the management of poultry health and welfare. Methods such as Faster R-CNN, YOLO, and SSD are applied for object detection, automatic counting of chickens, vocalization classification, and disease diagnosis with high precision. Several models, such as CNNs and Residual Networks (ResNet), demonstrate remarkable performance for various tasks, including density estimation, recognition of feeding behaviors, and detection of sick chickens. Deep Reinforcement Learning (DRL) is not yet commonly used in this field, but it holds potential for more complex applications in managing poultry welfare.

3 Background

The Internet of Things (IoT) has paved the way for innovative solutions for managing and automating processes in various sectors, including agriculture and livestock. The use of devices such as the ESP32 and cloud platforms like ThingSpeak offers immense potential to improve efficiency, productivity, and management in poultry farming.

3.1 Internet of Things (IoT)

The Internet of Things (IoT) represents a network of interconnected devices capable of collecting and exchanging data, thereby transforming various sectors such as agriculture, healthcare, and industry. In agriculture, IoT plays a crucial role by enabling remote monitoring and control of essential parameters such as temperature, humidity, and air quality. Through this technology, control systems, such as those for feeding, ventilation, and lighting, can be automated to enhance production conditions. In poultry farming, IoT provides innovative solutions for real-time monitoring of environmental conditions and the health of birds. Integrated sensors and microcontrollers allow for tracking various parameters and automating management systems, reducing the need for human intervention. This automation optimizes resource use and minimizes disease risks by maintaining optimal living conditions for poultry, thus contributing to more efficient and productive management of poultry farms.

3.2 ESP32 Microcontroller

The ESP32 is a versatile and cost-effective microcontroller developed by Espressif Systems, widely used in IoT applications due to its computing capabilities, Wi-Fi and Bluetooth connectivity, and low power consumption. It features a dual-core Tensilica LX6 processor running at up to 240 MHz, 520 KB of SRAM, and up to 16 MB of external Flash memory. It provides Wi-Fi and Bluetooth 4.2 (BLE) connectivity, as well as various communication interfaces, including UART, SPI, I2C, I2S, CAN, and Ethernet. The ESP32 also includes up to 34 programmable GPIOs, ADCs, DACs, and built-in sensors, while offering advanced security features such as cryptography and memory encryption. With its low-power consumption modes, the ESP32 is particularly well-suited for applications in environments where power supply is limited. Figure 1 shows an ESP32 board.

Figure 1. ESP32.

In the context of poultry farms, the ESP32 proves to be extremely advantageous. Its low cost enables farmers, whether small or large, to install large-scale monitoring and control systems without significant financial investment, making advanced technologies accessible even with limited budgets. Its energy efficiency is also a major asset, allowing the microcontroller to operate on battery power for extended periods, which is ideal for agricultural environments where constant access to electrical power is not always feasible. Additionally, the ESP32 easily integrates into various development environments and IoT platforms, facilitating the creation of agricultural management systems capable of monitoring and controlling conditions in real-time via web or mobile interfaces. The ESP32 also offers advantages in wireless connectivity thanks to its Wi-Fi and Bluetooth capabilities, allowing multiple sensors and actuators to be connected without complex wiring. It supports various IoT protocols such as MQTT, HTTP/HTTPS, and WebSocket, ensuring secure communication between devices. By integrating security features like AES cryptography and secure boot, the ESP32 ensures data reliability and protection against intrusions, which is crucial for preventing economic losses due to failures or cyberattacks. In summary, the ESP32 is an ideal solution for modernizing poultry farms, enabling more efficient, economical, and sustainable management of the farming environment.

3.3 YOLOv7

YOLOv7, an advanced version of the well-known object detection model You Only Look Once, stands out due to its significant improvements in accuracy, speed, and flexibility. Compared to its predecessors like YOLOv4 and YOLOv5, YOLOv7 introduces architectural optimizations, such as more efficient convolutional layers and advanced normalization techniques, allowing for finer and faster object detection in complex images. This version is particularly suited for real-time detection applications, where analysis speed and precision are essential. When applied to the detection of regions of interest in fecal images captured by cameras, YOLOv7 can accurately identify specific characteristics of fecal samples, even in low-contrast conditions or in the presence of debris. This ability to detect subtle details in real time is crucial for monitoring animal health indicators and for proactively managing the welfare conditions of poultry. By integrating YOLOv7 into a camera-based monitoring system, producers can enhance the quality of collected data, leading to improved decision-making and optimized resource management.

3.4 MobileNetV3

MobileNetV3 is an advanced convolutional neural network architecture designed to provide an optimal balance between performance and efficiency. It relies on innovative techniques such as depthwise separable convolutions and expansion blocks to capture

(a) (b) (c)

Figure 2. Examples of images from the fecal image dataset. (a) Coccidiosis. (b) Healthy State. (c) Salmonella.

relevant features while minimizing computational complexity. MobileNetV3 comes in two variants: MobileNetV3-Large, which is optimized for increased performance in terms of accuracy and processing capacity, and MobileNetV3-Small, specifically designed for resource-constrained environments, offering a trade-off between model size and inference speed. The architecture of MobileNetV3 also integrates non-linearity modules such as ReLU6 and expansion convolution blocks to enhance feature extraction while maintaining a reduced memory footprint. Due to its efficient approach to network architecture, MobileNetV3 is particularly well-suited for applications such as image classification on mobile or embedded devices, where speed and efficiency are crucial. Using MobileNetV3 for moderate-sized datasets, such as those with 8,067 images, allows for high-quality results while optimizing computational resources and energy consumption.

3.5 Dataset

A data set of 8,067 images of annotated poultry feces was obtained from the open database Zenodo [46]. These images come from the Arusha and Kilimanjaro regions in Tanzania and were collected between September 2020 and February 2021 using the Open Data Kit (ODK) mobile application. The dataset is organized into four distinct categories: "healthy," "salmonellosis," "coccidiosis," and "Newcastle disease." Table 1 summarizes the size of each class, and Figure 2 presents some example images from the fecal image dataset:

Table 1. Size of each class in the database.

Class	Number of Images	Percentage
Salmonella	2625	32.54%
Coccidiosis	2476	30.69%
Healthy	2404	29.8%
Newcastle Disease	562	6.96%
Total	8067	100%

4 Methodology of the System

The proposed system integrates various sensors (temperature, humidity, gas, water level, etc.), microcontrollers (ESP32), relay modules, a servo motor, and other electronic components. These sensors collect environmental data, which is transmitted to a cloud via Wi-Fi. The overall conditions are then monitored and managed automatically by the developed system. All data is stored in the ThingSpeak cloud database for in-depth analysis, allowing for useful insights and notifications to be received. Optimal values for maintaining the health and performance of the poultry are determined from the stored data, which also helps in forecasting future conditions. Meanwhile, a system is employed to monitor the health parameters of the poultry, as illustrated in Figure 3.

The collected data is analyzed using two artificial intelligence algorithms: Yolov7 to segment regions of interest from the fecal images captured by cameras, and MobileNetV3 to classify these images into four health statuses: healthy, coccidiosis, salmonella, and Newcastle disease.

The cloud enables bidirectional communication, as

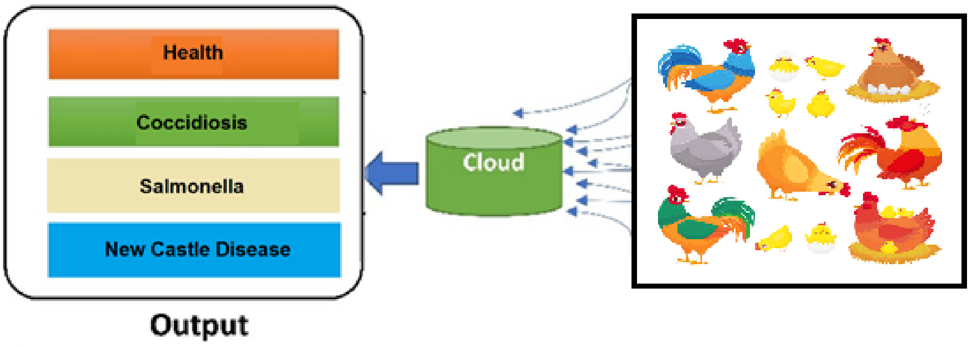

Figure 3. Architecture of the proposed intelligent poultry monitoring system.

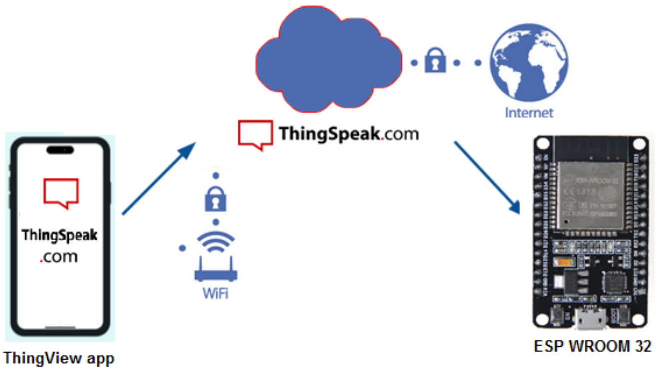

Figure 4. Communication diagram between the smartphone and ESP32 via the Cloud.

illustrated in Figure 4. First, all electrical devices on the farm, such as doors, lights, and fans, are automated and can be controlled remotely via Wi-Fi using a smartphone and the internet. Second, the user can receive real-time information about the status of the farm. The data, transmitted to the cloud by the ESP32 from various sensors, is then displayed on the user's phone. Monitoring, analysis, and control can be performed from anywhere in the world. Notably, our proposed system sends data and notifications via email and SMS.

The comfort of the chickens is ensured by an automatic control system. The user can set thresholds for temperature, humidity, and water level. When the temperature exceeds the defined threshold, the fans and cooler automatically activate. Conversely, if the temperature drops below the threshold, the heating system starts. Additionally, if the water level in the reservoir decreases, the pumps automatically turn on to replenish the water. The lighting and fan are regulated based on the temperature. When the temperature is below 20 °C, all heating indicators light up. Conversely, when the temperature reaches 24 °C, the heating indicator automatically turns off, and the cooling fan activates to regulate the temperature. This temperature threshold can be adjusted by the user.

5 Infrastructure of the Poultry Farm System

5.1 Hardware Design

The hardware infrastructure of a poultry farm is based on an ESP32 development board. This section details the various hardware components connected to this device. Figure 5 presents a functional representation of the poultry farm system using the ESP32.

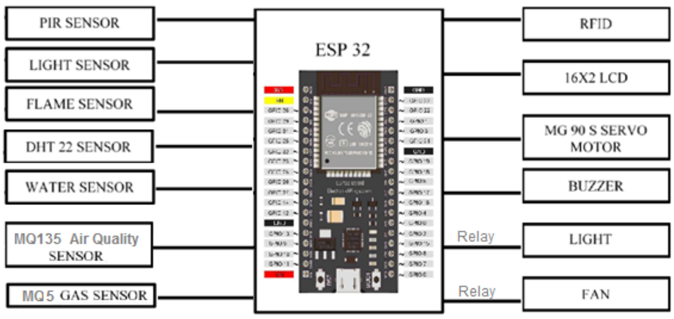

Figure 5. Functional representation of the poultry farm system using the ESP32.

According to the functional diagram presented in Figure 5, the ESP32 board is connected to various components, such as sensors, an RFID module, a lamp, an LCD screen, and a fan. The RFID system (radio-frequency identification) is used to verify the authenticity of users access cards, while the 16x2 LCD screen displays a welcome message and the identification number of each scanned RFID card. The MG 90 S servo motor automatically opens and closes the door when the RFID module detects a valid card. In case of an emergency, such as a fire, flood, or gas leak, a buzzer alerts the occupants of the farm. The lamp is installed to provide lighting, while a fan regulates the indoor temperature according to a programmed value.

Various sensors also play a crucial role in the system: the MQ5 gas sensor detects gas leaks and can identify different types of gases such as LPG, natural gas, and city gas. The water sensor identifies the presence of water to signal flooding, especially in sensitive areas. The DHT sensor measures temperature and humidity, while the flame sensor detects the presence of flames to prevent fires. The DHT sensor allows for continuous monitoring of the conditions in the chicken coop. A temperature below 20 °C (70 °F) can be fatal for chicks, and inadequate humidity can affect their breathing. The optimal humidity range for poultry is between 60% and 80%. The light sensor measures the level of indoor brightness, and the PIR sensor is used to detect movements, thereby enhancing the security of the poultry farm. The inexpensive PIR motion sensor detects the presence of humans or animals around a chicken coop. Birds, especially the younger ones, are at risk of predation by animals like cats and dogs, as well as theft by people. Installing a PIR motion detector is therefore essential for monitoring any unwanted presence around the chicken coop. The MQ135 air quality sensor detects a variety of gases, including ammonia (NH_3), nitrogen oxides (NO_x), alcohol, benzene, smoke, and carbon dioxide (CO_2). The system also includes an insect-repelling device that uses ultrasound. These interconnected components enable efficient and secure management of the indoor environment.

5.2 Electrical Supply of the Poultry Farm

The electrical supply in the proposed system is designed from renewable energies, with a particular focus on solar energy, in order to provide a sustainable and environmentally friendly solution. By harnessing solar energy, poultry farms can meet various energy needs, such as lighting, heating, ventilation, and powering automation systems, using photovoltaic panels to convert sunlight into electricity and solar thermal systems to generate heat. This approach significantly contributes to the reduction of greenhouse gas emissions by minimizing the carbon footprint associated with traditional electricity production methods. Moreover, solar installations, combined with storage batteries, ensure a stable and continuous power supply, even in rural or remote areas away from the main power grid, thus enhancing the farm's energy independence. Finally, despite potentially high initial investment costs, long-term operating costs are low due to the absence of fuel expenses and reduced maintenance, making solar energy economically attractive and providing an improved return on investment over time. It is noted that backup energy and energy consumed during the night are stored in batteries during the day.

6 The Proposed Intelligent Health Monitoring System for Poultry

This research integrates an automated system for the detection and classification of poultry diseases based on the Internet of Things (IoT) and ThingSpeak. The system uses IoT sensors to collect real-time images of poultry droppings, which are then analyzed to predict the presence of the three most common poultry diseases: salmonellosis, coccidiosis, and Newcastle disease. The collected data, including classification results and confidence scores, are transmitted to ThingSpeak, where they are stored and visualized in real time. The development of this system includes the collection and preprocessing of image datasets via connected devices, the creation of augmented images, segmentation of the region of interest, and the training and testing of a deep learning model for image classification, as shown in Figure 6.

By integrating ThingSpeak, the system also offers a centralized management interface that allows for remote monitoring and analysis of poultry health data, thus facilitating proactive management and rapid disease detection.

6.1 Image Preprocessing

Image preprocessing is essential for enhancing the performance of computer vision models. Common steps include resizing images to a uniform size, normalizing pixels to accelerate learning, and data augmentation (rotation, cropping, noise) to reduce overfitting. Other techniques include color standardization, whitening to reduce redundancy, and noise reduction to improve feature quality. These methods help models learn effectively and generalize well to unseen data. In our study, region of interest (ROI) segmentation and data augmentation were performed on the images before introducing them into the deep learning classification model.

6.2 Extraction of the Region of Interest (ROI)

ROI extraction is a technique used in image processing to isolate the area of interest from the rest of the visual content. In this work, the YOLO v7 (You Only Look Once, version 7) object detection method was used

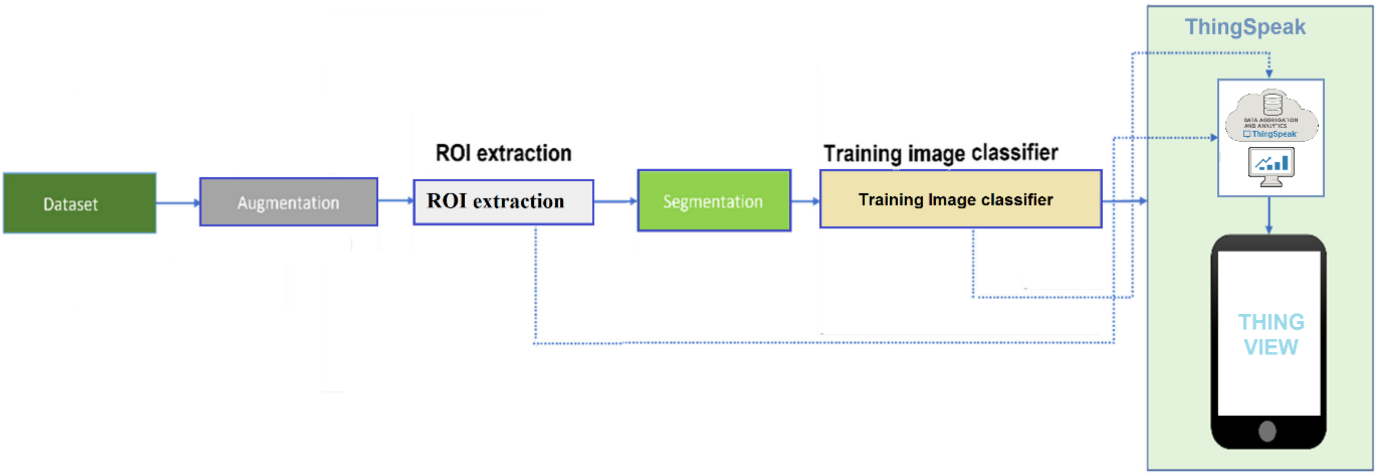

Figure 6. Summary diagram of the proposed system.

Table 2. Results of the poultry disease classification model with various performance metrics.

Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Precision	Recall	F1 Score
0.9963	0.9945	0.0149	0.0286	0.9934	0.9957	0.9946

instead of YOLO v3, after being trained on annotated datasets, to identify ROIs from images of feces. YOLO v7 is a real-time object detection algorithm that enables the identification of specific objects in videos, live streams, or still images. The algorithm utilizes features extracted by a deep convolutional neural network and advanced image processing techniques to identify objects in a given scene. YOLO v7 first divides an image into a grid. Each cell in this grid predicts several bounding boxes (or anchor boxes) around objects that exhibit a high score for predefined classes. Each bounding box is accompanied by a confidence score, representing the accuracy of the prediction, and detects a single object per box. The bounding boxes are generated by aggregating the dimensions of the ground truth areas from the original dataset to identify the most common shapes and sizes.

6.3 Training of the MobileNetV3 Model

Training a model from scratch requires a considerable number of images and significant computational resources, such as high-performance processors. To address these requirements, transfer learning is an effective approach. This technique involves adapting and reusing a pre-trained model on a large dataset to reorient it towards a new task. By doing so, it is possible to leverage the knowledge already acquired by the model, which reduces the need for large datasets and decreases training time. It should be noted that the model training was conducted offline, and the weight files were converted from a format readable by the training framework to a format compatible with the ThingSpeak platform.

7 Experimental Results and Discussion

7.1 Performance Evaluation Criteria

The performance evaluation criteria for the models are varied and depend on the task and objectives. Several indicators are commonly used to measure these performances. The first indicator is accuracy, which evaluates the proportion of correct predictions relative to the total number of predictions. This indicator is particularly relevant when the classes are well balanced. Other important criteria include precision, recall, and F1-score. Precision refers to the proportion of true positive predictions among all positive predictions made by the model. Recall, on the other hand, measures the model's ability to correctly identify true positives among all actual positive cases. These indicators provide a better assessment of performance in situations where classes are imbalanced.

7.2 Experimental Results

The image classification model employed was trained on a set of annotated images, using a data split of 85% for training and 15% for testing. Training was conducted over 80 epochs, allowing the model to learn effectively from the available data. The results show that the model achieved an impressive accuracy of 99.3%, a recall of 0.9957, and an approximate F1-score of 0.9946. This high accuracy indicates not only remarkable performance in correctly classifying images but also significant robustness against data variability. Table 2 presents a comparison of performance in terms of training and validation accuracy/error, as well as precision, recall, and F1-score.

Regarding the extraction of the region of interest (ROI), the YOLO v7 model was trained on a fully annotated dataset. The training used a data split of 85% for training and 15% for testing, allowing for a thorough and rigorous evaluation of the model's performance. The process was carried out over 150 epochs, a duration that ensured the model had sufficient time to learn and adjust to the characteristics of the objects to be detected. At the end of this training, the model demonstrated notable performance with an average loss of 0.14, indicating good generalization capability and low error in object prediction. Furthermore, the model achieved an average mean Average Precision (mAP) of 89.84%, a key indicator of the accuracy and relevance of detections. These results highlight not only the effectiveness of the YOLO v7 model but also the importance of annotation quality and hyperparameter optimization in achieving high performance.

7.3 Discussion

Our work is not among the first attempts to address the detection and classification of poultry diseases from images of poultry droppings using deep learning techniques, as many research projects have preceded us. However, what significantly distinguishes our work is the high classification accuracy we achieved compared to previous research. This superiority is a direct result of the multiple improvements made to the methodology and techniques used.

Among the major improvements we introduced is the use of the Yolov7 object detection algorithm instead of YOLO-V3. Yolov7 is an updated and more efficient version of YOLO-V3, offering better accuracy and greater speed in detecting and classifying objects in images. This has significantly improved our system's performance in accurately identifying poultry diseases.

Additionally, we used the pre-trained MobileNetV3 image classification model instead of ResNet50. MobileNetV3 stands out for its efficiency and speed in processing images while consuming fewer resources, making it an ideal choice for applications requiring high classification accuracy and rapid execution. This model is also designed to be easily deployed on devices with limited processing capabilities, such as those used in farms.

Another key element of our system is the integration of ThingSpeak, an IoT (Internet of Things) platform that enables real-time collection, storage, analysis, and visualization of data. ThingSpeak provides us with the advantage of remotely monitoring critical parameters of the poultry farm, such as temperature, humidity, and levels of lighting and feeding. Through this platform, collected data is sent in real time, allowing for quicker decision-making and immediate responses to urgent situations. Moreover, ThingSpeak facilitates centralized data management from multiple sensors, thus providing a comprehensive overview of the farm's status.

In addition to these technical improvements, our work is also distinguished by the integration of a comprehensive poultry farm management system. This system is not limited to disease detection from droppings images but also extends to monitoring farm conditions, such as temperature, humidity, as well as managing feeding and lighting. With the integration of ThingSpeak, this system offers a complete and intelligent solution for managing farms more effectively while enhancing poultry productivity and health.

In summary, our work stands out from previous research in four main aspects: higher classification accuracy achieved through the use of modern technologies such as Yolov7 and MobileNetV3, faster and more efficient performance, integration of ThingSpeak for real-time monitoring, and an integrated farm management system.

8 Conclusion

The proposed intelligent poultry system, integrating IoT and deep learning technologies, offers an innovative and effective solution for the early detection of poultry diseases from fecal images and remote farm management. By utilizing IoT sensors, the ESP32, and the ThingSpeak platform, this system allows for real-time monitoring of environmental conditions and poultry health while reducing operational costs. The Yolov7 and MobileNetV3 algorithms demonstrated remarkable accuracy in detecting and classifying diseases, significantly improving poultry productivity and welfare. The experimental results show robust performance, making this system viable for large-scale application in the poultry sector. This approach thus contributes to proactive farm management, minimizing economic losses and optimizing resource utilization.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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