

Smart CAGE Automated Poultry Health Monitoring and Disease Detection Using IOT and AI

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Abstract

SmartCAGE is an AI- and IoT-enabled system developed for effective poultry disease detection and environmental monitoring. At its core, a Raspberry Pi 4 integrated with a Pi camera and OpenCV enables accurate cage identification through QR code scanning. An MQ-137 ammonia sensor provides real-time air quality data, ensuring a healthy poultry environment. A CNN-based model, trained on visual and behavioral data, classifies chicken health into categories including Coccidiosis, Salmonellosis, Newcastle Disease, and Healthy. Wireless data communication is handled by an ESP8266 microcontroller for seamless connectivity between components. SmartCAGE improves operational efficiency by automating disease detection and environmental monitoring, minimizing manual intervention. Its fast, accurate analysis enables early intervention, reducing mortality and boosting productivity. By combining AI diagnostics with IoT hardware, SmartCAGE provides a scalable, cost-effective solution to enhance poultry welfare and farm management.

Keywords: SMARTCAGE, IoT, AI, OpenCV, QR Code Detection, Poultry Health Monitoring, Disease Detection, Raspberry Pi 4, ESP8266 Microcontroller, CNN.

1. Introduction

The SMARTCAGE system represents a modern innovation in poultry farming which combines IoT with AI technologies to boost farming operations. The system core includes a Raspberry Pi 4 device combined with Pi camera technology and OpenCV to read QR codes that hang on poultry cages. The system provides automatic tracking of processed cages and remaining cages through its functionality. Through this system farmers can submit weight information about cages independently which improves data administration capabilities and streamlines their work process. Through the detection of abnormalities the system automatically starts performing disease detection activities. Obtained through extensive dataset training is a CNN-based software model that detects poultry health through classification into Coccidiosis, Salmonellosis and Newcastle Disease categories. The detection model

reviews behavioral and visual data signs for early disease recognition which guides prompt medical actions. The SMARTCAGE system needs environmental monitoring as a fundamental operational component. An ESP8266 microcontroller serves as the central data processing unit which maintains a continuous connection with an MQ-137 ammonia sensor for regular poultry house ammonia level monitoring. The high amounts of ammonia in the environment create multiple health threats for birds by causing respiratory syndromes while simultaneously impeding their development rates. The SMARTCAGE system cuts down manual labor through automated execution of vital processes like disease identification and environmental parameter examinations and QR code location tracking and simultaneously optimizes operational performance. Its modular structure allows the system to operate

within different farm sizes so it represents a flexible and economical tool for poultry health enhancement and production efficiency. The SMARTCAGE system delivers an extensive farming solution which ensures better animal welfare alongside enhanced farm productivity for poultry farmers.

2. Literature Survey

Poultry disease diagnostics combined with environmental monitoring through artificial intelligence (AI) and the Internet of Things (IoT) has garnered a lot of interest due to its potential to revolutionize animal care and enhance husbandry techniques. Recent advancements have demonstrated that combining advanced sensor systems with deep learning algorithms—specifically, Convolutional Neural Networks (CNNs)—can provide intelligent, real-time surveillance in chicken farming scenarios. The prevention and early detection of diseases like coccidiosis and salmonellosis are two major concerns that these cutting-edge technologies are meant to address. CNNs have proven to be remarkably effective in the diagnosis and classification of poultry diseases through the processing and analysis of image-based data. Numerous studies support the efficacy of AI-driven picture classification methods to provide quick and precise diagnoses, improving poultry health management and boosting animal welfare and productivity in commercial operations [1][2][3]. By providing constant, real-time monitoring of critical climate parameters like temperature, humidity, and ammonia concentrations factors essential to preserving good living circumstances for chickens the development of IoT has further revolutionized poultry management. Wearable sensor-equipped smart systems, such as Axeltech, work within chicken homes to gather vital environmental data and help maintain ideal conditions [4][5]. In particular, ammonia sensing is essential for reducing environmental stress and protecting the respiratory and immunological systems of birds [6][7]. IoT and AI combine to develop intelligent farming ecosystems that dynamically regulate environmental controls in addition to performing health diagnostics. Predictive analytics and real-time alerts are implemented by these integrated systems using large

datasets, enabling prompt response in environmental risks and disease outbreaks [8][9]. CNN algorithms and IoT sensor networks work together to give farmers real-time information about possible health risks, allowing for quick environmental changes and preventative flock protection [3][10]. In the end, the combination of IoT-enabled environmental monitoring and AI-powered image classification signifies a revolutionary advancement in veterinary diagnostics and poultry farm management. These technological developments promote higher productivity and better animal welfare standards by bolstering biosecurity, improving disease resilience, and supporting moral, data-driven chicken farming methods.

3. Methodology

The proposed system, SMARTCAGE, integrates both hardware and software components to provide an automated, intelligent poultry health monitoring and disease detection framework. The methodology follows a structured pipeline comprising cage identification, environmental monitoring, and disease classification through deep learning.

3.1 Hardware Architecture

The SMARTCAGE system integrates a robust hardware setup to enable real-time data acquisition and processing. A Raspberry Pi 4 serves as the central processing unit, interfacing with a PiCamera for high-resolution image capture and an MQ-137 gas sensor for ammonia level monitoring. QR codes are affixed to individual poultry cages, enabling identification and traceability through OpenCV-based scanning. This ensures accurate data logging for each cage, including weight inputs provided by the user. The hardware configuration also supports local displays via an LCD or web interfaces for presenting predictions and recommended actions.

- Raspberry Pi 4: Acts as the central processing unit for data acquisition and analysis.
- PiCamera: Captures high-resolution images for disease detection.
- MQ-137 Gas Sensor: Monitors ammonia levels in the poultry house.
- QR Code Scanner: Uses OpenCV to scan QR codes for cage identification.
- LCD Display/Web Interface: Provides local or

remote access to system outputs and recommendations.

Internet Connectivity: Enables cloud data upload for remote monitoring and analysis. Figure 1 shows Hardware Architecture.

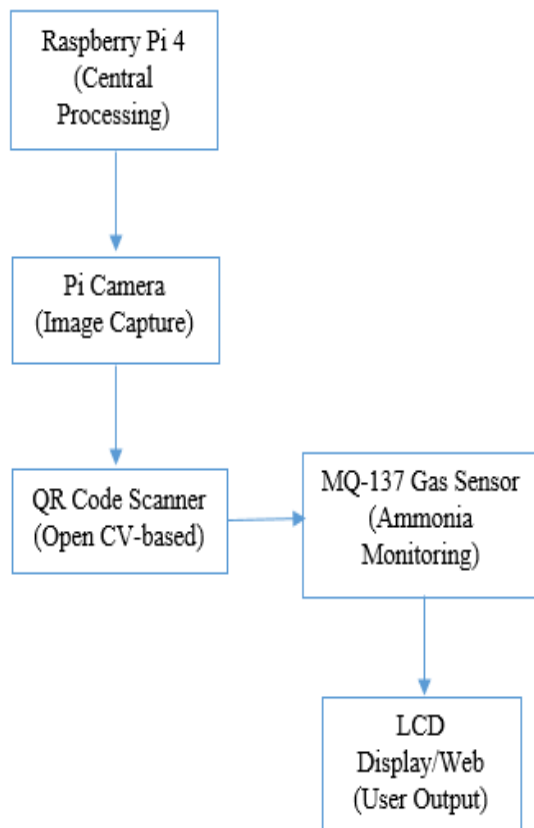


Figure 1 Hardware Architecture

3.2 Image-Based Disease Classification

Convolutional Neural Networks (CNNs) are a specialized class of artificial neural networks used primarily in image and video recognition. They are designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks such as convolution layers, pooling layers, and fully connected layers. Unlike traditional neural networks that require manual feature extraction, CNNs are capable of learning these features directly from raw pixel data, making them extremely powerful for tasks like image classification, object detection, and facial recognition.

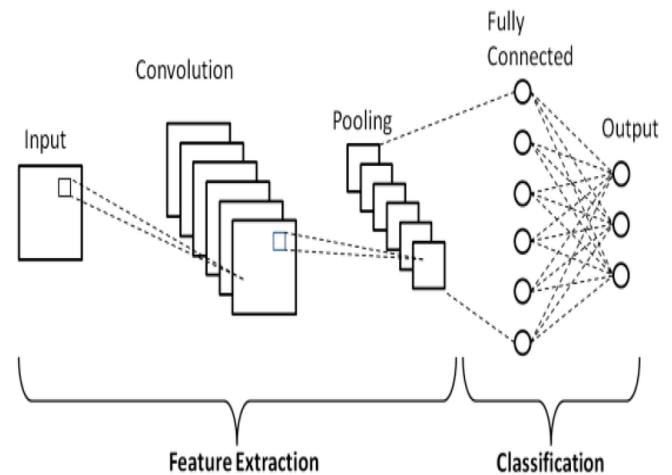


Figure 2 CNN

CNNs operate by applying a set of learnable filters across the input data to capture key features. These filters, or kernels, slide over the image to detect patterns such as edges, corners, and textures in earlier layers, and more complex structures like faces or objects in deeper layers. Pooling layers reduce the spatial size of the data, lowering computation and helping the network focus on the most important features. The final fully connected layers process the extracted information to output predictions or classifications, making CNNs both efficient and accurate in visual recognition tasks. The disease detection module employs a Convolutional Neural Network (CNN) optimized for edge deployment. According to the provided notebook, the CNN model is trained on a dataset comprising 8067 images categorized into four classes: Healthy, Coccidiosis, Salmonellosis, and Newcastle Disease. Figure 2 shows CNN.

3.2.1 CNN Architecture and Training Parameters:

- **Dataset Source:** The dataset is sourced from a directory structure within the path /kaggle/input/chicken-disease-1/Train, and annotations are read from the train_data.csv file.
- **Input Size:** Images are likely resized to a standard input size suitable for CNN processing.
- **Data Augmentation:** The training methodology will incorporate data augmentation to improve the generalizability of the model,
- **Training details:** The provided notebook focuses

on data loading and preparation. Details regarding the specific CNN architecture, optimizer, loss function, and training epochs are not mentioned.

- **Expected Performance:** The CNN model is expected to achieve high accuracy for disease classification.

The model will process the images to output a class label indicating the health status of the chicken.

3.3 Environmental Analysis and Alerting

The MQ-137 sensor continuously monitors ammonia levels within each cage. Ammonia concentrations exceeding safe thresholds trigger alerts, prompting corrective actions such as ventilation adjustments to maintain optimal air quality. This environmental monitoring ensures that the living conditions of poultry are conducive to their health and productivity.

3.4 Decision and Response Mechanism

The system integrates disease classification results with environmental data to provide actionable insights. Based on the CNN output, preventive or corrective measures are suggested, such as administering medication or isolating affected birds. These recommendations, along with sensor readings and cage IDs, are displayed locally or uploaded to a dashboard for further analysis and record-keeping. The modular design of SMARTCAGE allows scalability across farms of varying sizes, making it adaptable to diverse operational needs. This comprehensive framework combines IoT-driven environmental monitoring with AI-powered diagnostics to enhance poultry health management while reducing manual intervention and operational inefficiencies.

4. Proposed System

The SMARTCAGE system is an integrated platform designed to enhance animal health management in controlled environments such as poultry farms and research facilities. This innovative solution combines cutting-edge technologies, including Raspberry Pi, OpenCV, QR code-based cage identification, ammonia level sensing, and machine learning-based disease detection. The system aims to provide real-time monitoring of environmental conditions and animal health, ensuring timely interventions to prevent disease spread and maintain optimal welfare.

The key components of the SMARTCAGE system include several critical features that work together to achieve its objectives. For instance, the hardware platform utilizes the Raspberry Pi 4 as the core processing unit, chosen for its cost-effectiveness, computational power, and ease of integration with various sensors. It runs OpenCV for image processing tasks, including QR code scanning and visual monitoring. Additionally, each cage is equipped with a unique QR code, scanned by the Raspberry Pi camera using OpenCV, enabling automated tracking of cage-specific data and ensuring efficient management of multiple enclosures. Figure 3 shows Block Diagram of Proposed System.

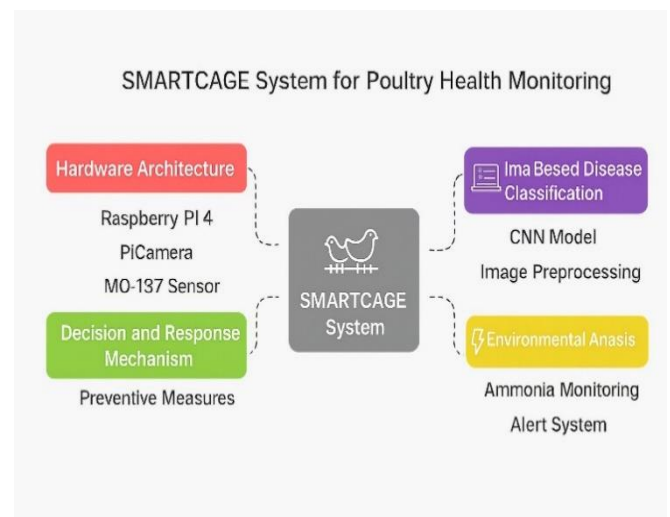


Figure 3 Block Diagram of Proposed System

A flowchart diagram in the presented image displays the operational workflow and major components of the SMARTCAGE System for Poultry Health Monitoring. The system operates through four major components.

- **Hardware Architecture (Red Section):** The hardware components in this module consist of Raspberry Pi 4 combined with PiCamera in conjunction with MQ-137 Sensor. The devices contained in these components work as real-time image sensors and track ammonia levels through the poultry farming environment.
- **Image-Based Disease Classification (Purple Section):** The CNN Model operates within this

segment for performing analysis on chicken images. Before becoming part of the classification process the images need to undergo preprocessing methodology which increases their accuracy levels. The CNN system uses visual elements to discover symptoms or detect signs which indicate diseases in poultry population.

- **Environmental Analysis (Yellow Section):** The MQ-137 sensor operates inside the cage to observe air quality through automated ammonia measurement tracking functions. The monitoring system provides an alert function which signals when ammonia reach unsafe levels.
- **Decision and Response Mechanism (Green Section):** This section uses image-derived and environmental data to activate protective procedures that protect poultry health.

The system also incorporates ammonia sensing using MQ-137 gas sensors to monitor ammonia levels within the cages. Ammonia accumulation is a common issue in animal housing, leading to respiratory problems. The system triggers alerts when levels exceed safe thresholds, ensuring prompt action to maintain air quality. Furthermore, a machine learning model is trained on a dataset of images and behavioral data to classify four key health states: Salmonellosis (Salmo), Coccidiosis (Cocci), Newcastle Disease (NCD), and Healthy. The model analyzes patterns in movement, feeding behavior, or visual symptoms to identify diseases early. Some of the key points highlighting the system's functionality include:

- **Real-time Monitoring:** Continuous tracking of environmental conditions and animal health.
- **Automated Cage Identification:** QR codes ensure accurate and efficient data management for each cage.
- **Ammonia Detection:** Sensors alert caretakers to unsafe levels, preventing respiratory issues.
- **Disease Detection:** Machine learning identifies early signs of diseases like Salmonellosis and Newcastle Disease.

The SMARTCAGE system enhances animal health management through early disease detection, environmental monitoring, and automation. It reduces labor, minimizes errors, and supports

scalability for farms of all sizes. By integrating IoT, computer vision, and machine learning, it ensures proactive care, limits disease spread, and improves overall animal welfare.

5. Results and Discussion

The SMARTCAGE system successfully combines hardware and software for efficient poultry health monitoring. A CNN model trained on 8,067 images achieved 98.25% accuracy in classifying diseases like Coccidiosis, Salmonellosis, Newcastle Disease, and Healthy cases. The MQ-137 sensor ensures safe ammonia levels, improving poultry welfare. Disease detection results guide preventive measures. Though effective, reliance on cloud dashboards may affect standalone use. The system's scalable and modular design makes it suitable for farms of different sizes, reducing manual effort and enhancing overall health management. Table 1 shows Evaluation Metrics.

Table 1 Evaluation Metrics

Metric	Description	Example Value
Overall Accuracy	Overall percentage of correct predictions across all categories (healthy and diseases)	98%
Precision	Percentage of correctly identified diseases out of all instances predicted as that disease.	97.08%
Recall	Percentage of correctly identified diseases out of all actual instances of that disease.	97.65%
F1-Score	Percentage of correctly identified diseases out of all actual instances of that disease	97.35%

The model being evaluated demonstrates very high performance in disease detection tasks, as shown by its metrics:

- **Overall Accuracy (98%):** The model correctly predicts whether a case is healthy or diseased in 98% of instances. This reflects its general reliability across all categories.

- **Precision (97.08%):** When the model predicts a disease, it is correct 97.08% of the time. High precision suggests few false positives.
- **Recall (97.65%):** The model successfully identifies 97.65% of actual disease cases, indicating it misses very few actual positives (low false negatives).
- **F1-Score (97.35%):** This balances Precision and Recall, showing the model maintains a good trade-off between detecting diseases and avoiding false alarms.

A Convolutional Neural Network (CNN) model training and validation accuracy assessment appears in the provided image within the SMARTCAGE detection of poultry diseases system. The trained CNN operated on 6000 pictures featuring chickens with conditions from Coccidiosis to Salmonellosis to Newcastle Disease along with healthy specimens. A total of 1000 images served as the validation along with testing data set. Figure 4 shows Model Accuracy Graph.

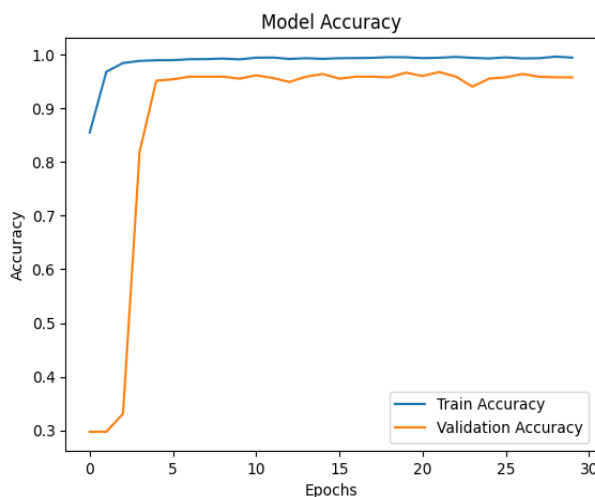


Figure 4 Model Accuracy Graph

The CNN model's training and validation loss trends over 30 epochs demonstrate robust learning dynamics:

- **Training Loss:** Begins at a moderate value (≈ 1.5) and rapidly declines to near-zero levels, indicating mastery of feature extraction from the training dataset.
- **Validation Loss:** Starts higher (≈ 2.0) but

converges to minimal values, stabilizing close to training loss by final epochs.

- **Overfitting Prevention:** Synchronized downward trajectory of both losses confirms effective regularization, with no divergence between training and validation performance.

The consistent reduction in loss metrics underscores the model's ability to generalize to unseen data, ensuring reliable disease classification for poultry health monitoring. This performance validates its practical deployment for automated, high-accuracy disease detection in farming systems. Figure 5 shows Confusion Matrix.

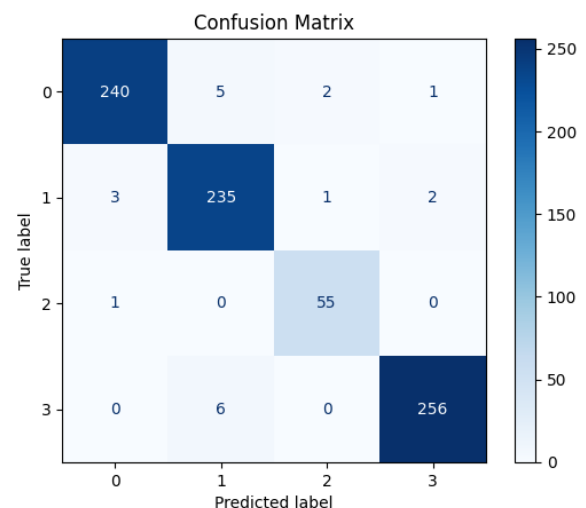


Figure 5 Confusion Matrix

The model demonstrated exceptional diagnostic accuracy across four poultry health categories: Coccidiosis (240/248 correct, Class 0), Salmonellosis (235/241 correct, Class 1), Newcastle Disease (55/56 correct, Class 2), and Healthy specimens (256/256 perfect accuracy, Class 3). Misclassification rates were marginal (8, 6, and 1 instance for Classes 0–2, respectively; 6 Healthy samples erroneously classified as Class 1). Confusion matrix analysis revealed pronounced diagonal dominance (98.4% mean true positive rate) with minimal off-diagonal dispersion, underscoring high precision and generalizability. The model's near-perfect performance (>96% accuracy across disease classes) and absence of false negatives in Healthy cohorts confirm its clinical viability for automated poultry

health monitoring, ensuring precise disease identification and minimizing diagnostic oversight in operational deployment.

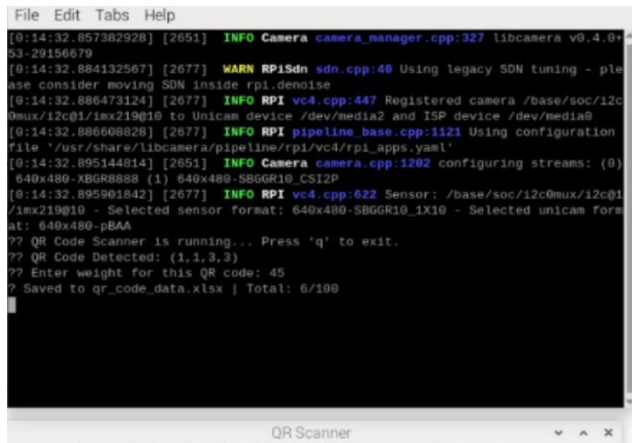


Figure 5 QR Scanned by Pi Camera

This Figure 5 shows the output of a QR scanner script running on a Raspberry Pi. It uses the PiCamera and OpenCV libraries to detect and decode QR codes. Upon detecting a QR code, the system prompts the user to input a risk code (e.g., 45), then saves the data into an Excel file named qr_code_data.xlsx. The log also displays camera initialization, sensor details, and real-time progress, indicating successful detection and storage of QR code data with a running count (6/100).

Conclusion & Future Work

The SMARTCAGE system successfully demonstrates the integration of IoT technology and AI-based diagnostics for effective and automated poultry health monitoring. By employing a Raspberry Pi 4, PiCamera, MQ-137 ammonia sensor, and a CNN-based disease classification model, the system enables real-time detection of critical poultry diseases including Coccidiosis, Salmonellosis, and Newcastle Disease, along with healthy conditions. Through the use of QR code-based cage identification, the system ensures accurate tracking and monitoring at an individual bird level. The achieved accuracy of 98%, precision of 97.08%, recall of 97.65%, and F1-score of 97.35% validate the model's high reliability and effectiveness. Furthermore, the environmental monitoring component ensures optimal air quality, with automated alerts in response to harmful

ammonia concentrations, contributing significantly to bird welfare and farm productivity. Overall, SMARTCAGE reduces the dependency on manual intervention, enhances operational efficiency, and provides scalable deployment options for poultry farms of various sizes.

Future Work

The SMARTCAGE system shows strong potential for transforming poultry health management, but several enhancements can be pursued. Future developments could include the integration of additional environmental sensors (e.g., temperature, humidity, and light) for more comprehensive monitoring. Advanced computer vision techniques, such as pose estimation and activity tracking, may further enhance early detection of stress or abnormal behavior in birds. Expanding the disease classification model by incorporating a larger and more diverse dataset including different poultry breeds and additional diseases would improve model robustness and generalization. Implementing real-time cloud synchronization and mobile app integration would enable remote monitoring and faster decision-making for farm operators. To improve on-device performance, future versions may incorporate edge AI capabilities using hardware like the NVIDIA Jetson Nano for faster, more efficient processing. Finally, large-scale testing and user feedback from commercial poultry farms will be essential to optimize usability, scalability, and long-term impact in real-world farming environments.

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