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Poultry Farming Abnormality Detection using ESP32-CAM and OpenCV

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Abstract

This research studies the use of the ESP32-CAM module when combined with SSD MobileNet and OpenCV to detect abnormalities in chicken farm operations, including feather plucking and pecking caused by imprisonment. The ESP32-CAM works as a video streaming server, providing real-time monitoring and analysis. Two techniques are investigated: the first includes the ESP32-CAM acting as a video streaming server for browser clients, while OpenCV and SSD MobileNet process the video stream and send the results back to the server. A prototype user interface is constructed for management. The second option uses the ESP32-CAM as a video streaming server for Python clients, with the video stream being processed on the client side using SSD MobileNet and OpenCV. This dual strategy guarantees that poultry farm settings are securely monitored and controlled, while also increasing management efficiency and resolving behavioral concerns.

1. Introduction

Chickens' physical and psychological health suffers when they are deprived of important needs and behaviors like as walking, turning, exploring, engaging with, or avoiding others, or being able to rest in solitude and comfort. The chickens get upset as a result of their forced confinement, which causes feather pulling and pecking. In poultry management, beak cutting or debeaking is done to prevent such acts of frustration. They are reared as egg-producing robots, with the purpose of maximum output from each bird regardless of its genuine wellness. In large-scale commercial poultry operations, the chickens' well-being and the farm's overall economic sustainability are dependent on the early diagnosis of unusual behavior, diseases, stressors, and environmental conditions [1]. A timely reaction to these challenges is critical for decreasing losses and ensuring the animals' well-being. Traditional chicken health and behavior monitoring systems rely heavily on manual inspections, which are time-consuming, labor-intensive, and prone to human mistake. As a result, modern poultry farming technology that detects abnormalities in real time is in high demand.

This study aims to collect existing research on IoT and computer vision applications in farming, with a focus on environmental monitoring, farm protection, and animal management. This review reviews recent research to highlight current trends, improvements in technology, and areas in literature that require further review. The scope of this literature review includes the following areas:
- Automating Poultry Farm Management with Artificial Intelligence [2]
- ESP32 CAM Based Object Detection & Identification with OpenCV [3]
- Application of ESP32-CAM in Poultry Farming [4]

- Environmental Monitoring in a Poultry Farming Using an Instrument Developed with The Internet of Things Concept [5]
- Object Detection and Dimensioning using OpenCV. [6]

The use of OpenCV for detecting abnormalities in poultry monitoring enhances precision and robustness. This technology, applied in fields like medical and environmental research, leverages advances in computer vision to improve poultry welfare.

Image Processing Technique

Proper camera placement and a homogeneous background minimize visual distortion and viewpoint variation, ensuring consistent, noise-free images. Image recognition compares feature vectors of reference and input images to identify patterns. Object detection locates specific categories within images. Deep learning (DL) algorithms handle multi-class object recognition and semantic segmentation better than traditional machine learning.

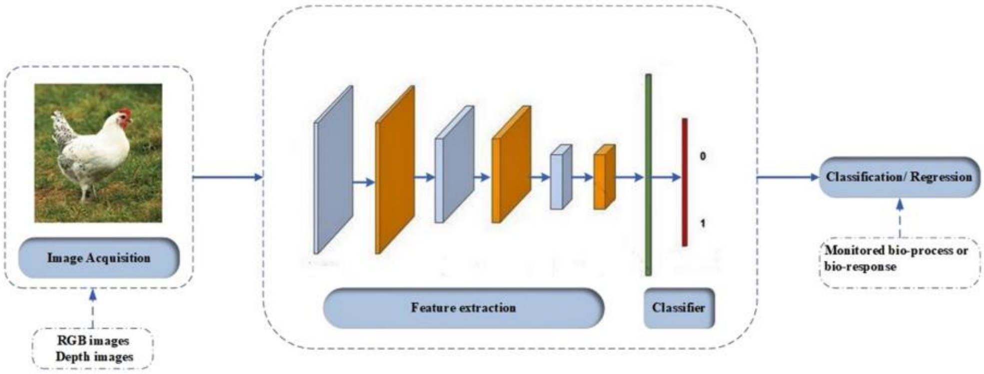


Fig. 1 General Workflow of Chicken Monitoring Systems.

Algorithms, Training Data, and Model Accuracy

- **Algorithms**: These include deep learning and machine learning-based systems for intelligent behavior promotion in poultry monitoring. Tasks include image collection, ROI segmentation, feature extraction, modeling, and classification. Deep learning is more accurate for large flocks.
- **Training Data**: Effective machine learning relies on carefully selected, varied, and representative training data. Accurate annotation is critical for developing systems that detect and respond to poultry abnormalities.
- **Model Accuracy**: Object shape and size help detect unwell broilers through posture analysis, with changes indicating diseases. Size correlates with health and growth, predicting factors like feed conversion ratio and market readiness. Morphological characteristics are key in object analysis due to their resistance to sensor noise and light/color insensitivity. Average system accuracy is calculated from multiple confidence scores, reflecting the system's certainty in detection.

2. Methodology

The method for detecting abnormalities in poultry using an ESP32-CAM, OpenCV, and SSD MobileNet includes a set of specific phases aimed at creating an accurate and effective system for real-time monitoring and alerting. The integration of several technologies offers a comprehensive strategy for automating the detection of potential issues in chicken production, resulting in timely interventions and improved the well-being of the livestock industry. This section details the systematic procedures used to build and execute the suggested system, such as the hardware configuration, software integration, data processing, model training and real-time alarm system.

In order to know the ESP32-CAM works smoothly to detect the stationary poultry, it has a few points,

i. Camera Positioning and Setup

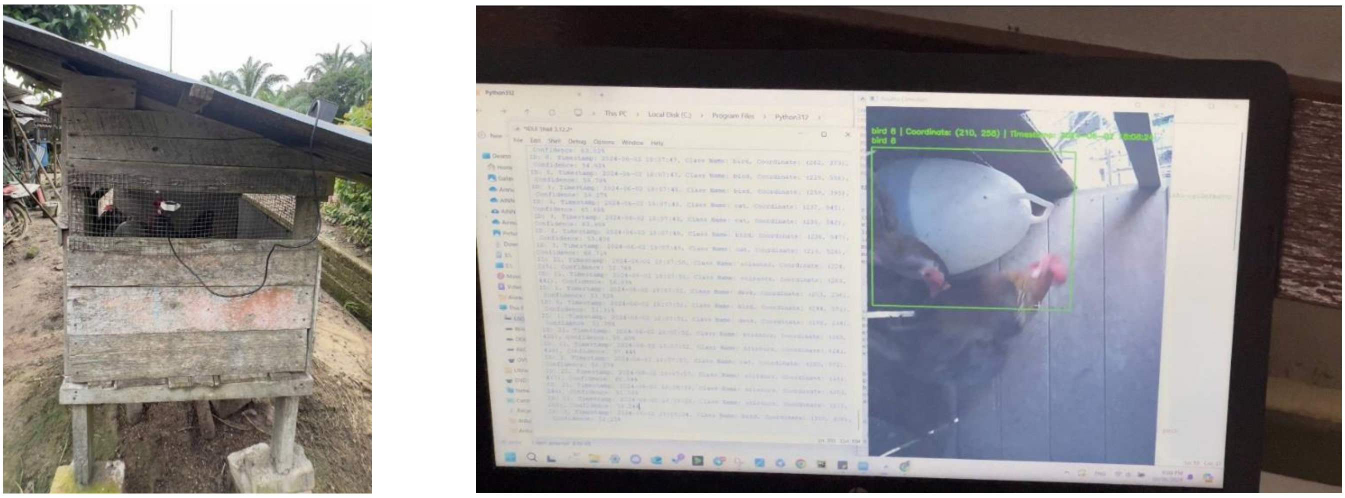
Proper placement of the ESP32-CAM is critical for efficiently covering the poultry area. The camera should be positioned at the proper angle and height to capture the full picture with minimal impediments as shown in Figure 2 (a), ensuring that each chicken is clearly seen. Careful consideration of the camera's area of vision helps to avoid blind spots in which poultry may go unnoticed. Consistent illumination is also required for clear and precise image capturing. While natural sunshine may be sufficient, continuous illumination reduces shadows and fluctuations, which might influence detection accuracy. For nighttime monitoring, infrared lamps should be utilized to obtain high quality photos without disturbing the poultry, allowing for 24-hour observation. This configuration increases the detecting system's reliability and performance at all times.

ii. Detecting Algorithms

Object Detection Models: Using real-time object detection models, SSD or MobileNet, the ESP32-CAM can reliably distinguish and detect poultry inside the frame as shown in Figure 2(b). These algorithms, which have been particularly trained to recognize poultry, have extensive detection capabilities, guaranteeing that each bird is correctly identified.

Stationary Detection Logic: Once chickens have been identified, logic must be added to follow their locations throughout numerous frames. Technology can assess whether any birds remain immobile by tracking their whereabouts over a set length of time. If a bird's position does not move for more than a certain amount of time, an alarm might be issued. This strategy guarantees that immobile poultry are identified in a timely manner, allowing for prompt reaction and control.

The data collection phase is fundamental to the efficacy of the proposed poultry farming abnormality detection system. This segment delineates the key considerations involved in acquiring relevant datasets utilizing the ESP32-CAM. documentation of these considerations ensures the reliability and representativeness of the dataset employed in subsequent stages of the research. Figure 1 shows the hardware placement.



(a) **(b)**

Fig. 2 *Figure description (a) The hardware placement; (b) Result for the Camera Placement*

3. Results, Analysis and Discussion

Analyzing system accuracy and delays are essential for the ESP32-CAM-based chicken identification and tracking system. System accuracy depends on the precision of image recognition algorithms, which are influenced by lighting conditions, camera resolution, and surroundings detail. High detection confidence levels indicate consistent performance, but low confidence levels might demand more algorithm improvements or improved camera location. For example, changing lighting conditions during the day could reduce the system's capacity to reliably detect and track hens, requiring new algorithms that can manage variable light intensities. At the same time, In a similar vein, camera placement matters. A camera in a good location ensures complete coverage and minimal problems, which enhances detection accuracy. The results of the accuracy and delay analysis play crucial roles in this project by providing actionable insights into the system's performance. High accuracy ensures that the system reliably identifies and tracks chickens, leading to effective monitoring of health and behavior. Accurate detection allows for early identification of abnormalities, such as illness or distress, enabling timely interventions that can prevent the spread of disease and improve overall flock health. Figure 3 below shows the system accuracy in detecting birds.

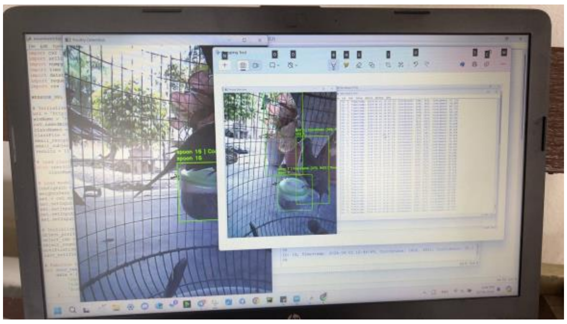


Fig. 3 Bird Detection

System latency, which is important for real-time monitoring, encompasses the time necessary for image collection, data processing, and transmission. Minimizing latency helps to ensure quick actions especially when spotting abnormalities or possible health concerns in poultry. The system's performance can be improved by improving the data processing line, installing faster processors, or developing more efficient data transfer protocols. Consistent testing and calibration help to identify limitations and increase overall efficiency, improving the system's dependability and usefulness in chicken farming. Regular algorithm upgrades, as well as periodic camera system recalibration, can solve any emergent accuracy and latency concerns.

Figure 3 shows that the system is relatively reliable, but there is still potential for development in terms of detecting algorithms, camera technology, and environmental management, making it more helpful for real-world poultry monitoring. Increasing the ability of the algorithms to account for numerous environmental conditions, such as dust and other animals' movement, could significantly improve detection rates. Furthermore, upgrading to higher-resolution cameras can result in sharper pictures, allowing for more precise identification and tracking.

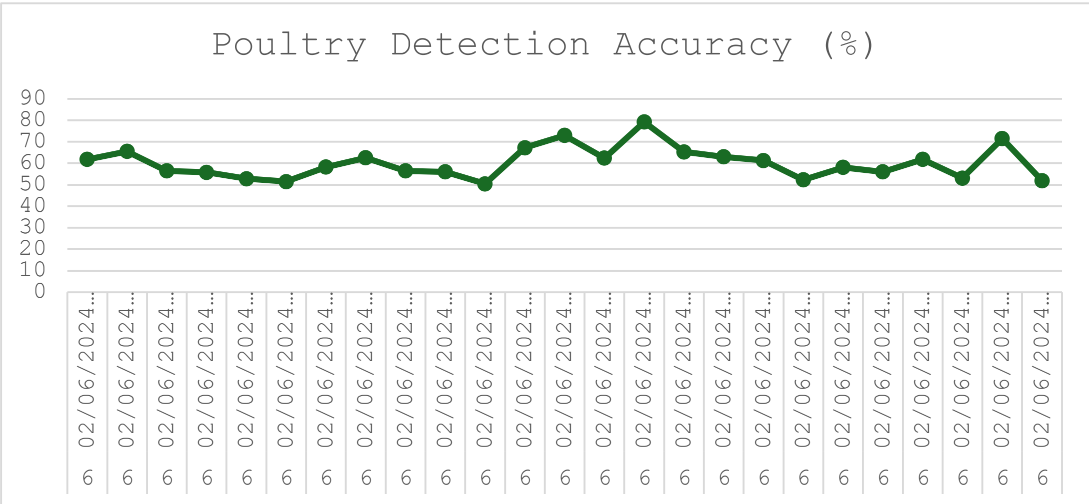


Fig. 4 Poultry Detection Graph

$$\text{Accuracy (\%)} = \frac{\textit{Total Success Images Detection}}{\textit{Total of Image Acquisition}} \times 100 \quad (1)$$

Based on Figure 4, the chart titled ‘Poultry Detection Accuracy (%)’ indicates that this chart represents the percentage of detection accuracy for a poultry identified with ID “6”. The Y-axis represents the detection percentage, ranging from 0 to 90%. The fluctuations in the line indicate changes in the detection accuracy over time. Meanwhile the X-axis represents the timestamps at which the detections were recorded.

The line chart displays the detection rate of a bird with ID 6 over a given time period. The line varies, demonstrating changes in detection accuracy at various timestamps. Initially, the detection rate hovers around 60%, indicating a moderate level of accuracy. As time passes, there is a notable grow, culminating about 70%. This peak denotes a time of high detection accuracy, during which the system successfully recognizes the bird.

However, there is a little fall after this peak, indicating probable discrepancies or difficulty in sustaining high accuracy.

4. Conclusion

The study is about choosing the best image processing techniques to develop a system that detects abnormality detection for poultry farming. SSD MobileNet V3 with OpenCV was used for this purpose. SSD MobileNet V3 was designed to provide both speed and accuracy, which makes it suitable for real-time object detection systems. SSD MobileNet v3 has been developed specifically for mobile and embedded devices, ensuring maximum performance even with limited processing capabilities like the ESP32CAM.

SSD MobileNet v3 improves in detecting small objects, which is critical for identifying particular problems like injuries or anomalies in poultry. This high level of precision is required to ensure the livestock's health and well-being. Furthermore, the lightweight nature of SSD MobileNet v3 enables efficient operation on the ESP32CAM, making it an achievable and effective option for continuous monitoring in limited resources.

The combination of OpenCV, an open-source computer vision library, allows for the handling of different image processing tasks required to prepare input for SSD MobileNet v3. OpenCV makes it easier to preprocess pictures by scaling and normalizing them, adding filters to improve image quality, and extracting features before feeding them into the detection model. The combination of ESP32CAM, OpenCV, and SSD MobileNet v3 creates an efficient, dependable, and automated system for monitoring poultry health and identifying abnormalities.

Acknowledgement

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This guide contains examples of common types of APA Style references. Section numbers indicate where to find the examples in the Publication Manual of the American Psychological Association (7th ed.).

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