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Chicken Health Detection System Using Edge Impulse with ESP32-Cam

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Abstract

The integration of technology in the agricultural industry has led to significant advancements in efficiency, productivity, and animal welfare. Efficiency, output, and animal welfare have all significantly improved as a result of technology's incorporation into agriculture. Poultry farming, particularly chicken rearing, is a critical sector that generates demand for improved detection systems to ensure chicken wellbeing. The Chicken Health Detection System, created using Edge Impulse and ESP32-Cam, is a groundbreaking project that aims to transform poultry health detection and management. This system uses image analysis to track the health of chickens in real time using IoT technologies and machine learning techniques. The system can differentiate between healthy and unhealthy chickens by integrating Edge Impulse and ESP32-Cam, providing poultry farmers significant details. The FOMO model was selected for its effective and accurate object detection and classification, especially in images with multiple objects. Its design optimizes performance on edge devices with limited computational power, making it suitable for real-time agricultural applications. The system's capacity to provide timely insights into the welfare of chickens demonstrates its potential to revolutionize current monitoring approaches, hence encouraging enhanced welfare standards and increased production within the poultry industry. The development and deployment of the Chicken Health Detection System represent significant accomplishments in the endeavor to modernize chicken farming operations. It showcases the ability of technology to address challenging agricultural problems and sets a foundation for future innovations in this domain. The system will gain value from strategic recommendations for enhancement, including expanding the dataset, enhancing hardware components, and exploring innovative methods for machine learning.

1.0 Introduction

The agricultural industry has seen a significant increase in the integration of technology to improve efficiency, productivity, and animal welfare. Poultry farming, particularly chicken rearing, is a crucial sector, driving the demand for advanced monitoring systems to ensure the well-being of chickens. The Chicken Health Monitoring System using Edge Impulse with ESP32-Cam is an innovative and practical project designed to enhance poultry farming by employing modern technologies. The project aims to create an IoT-based system capable of

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monitoring the health of chickens in a coop through image analysis. By integrating the ESP32-Cam microcontroller, Edge Impulse machine learning platform, and a dataset of chicken images, this system can distinguish between healthy and unhealthy chickens, providing valuable insights to poultry farmers.

The project requires a thorough background investigation covering various fields, such as posture, behavioral patterns, and feather condition. Understanding image processing techniques, such as feature extraction and classification algorithms, is essential when training models to differentiate between characteristics of sick and healthy chickens. Additionally, understanding hardware constraints and considerations, such as the ESP32-Cam's processing capabilities and power limitations, is equally important.

One of the biggest challenges is finding high-quality data to train the machine learning model, which requires a large dataset covering a range of chicken breeds, ages, and health situations. Another ongoing difficulty is guaranteeing the consistent quality and fineness of the gathered pictures under various environmental circumstances. Balancing the model's accuracy with its inference speed and memory usage becomes a crucial optimization problem.

Another major issue is interpreting chicken health indicators based only on visual data from the ESP32-Cam. The goal of this research is to create an effective model that can be used as a guide for project restoration. The objectives of this study include collecting a varied dataset of chicken pictures representing different ages, breeds, and health states, labeling and preparing the dataset for supervised machine learning using Edge Impulse, and employing the ESP32-Cam for real-time data capture and analysis to accurately classify chicken health.

2.0 Materials and methods

2.1 Materials

The Chicken Health Detection System is a cutting-edge integration of Edge Impulse and ESP32-Cam, designed for real-time monitoring of chicken health. Utilizing Edge Impulse's machine learning models, the ESP32-Cam captures and analyzes chicken health data, detecting anomalies in behavior. The system uses sensors and advanced algorithms to provide real-time alerts to farmers or poultry management. The user-friendly interface ensures easy implementation and seamless integration into poultry farming practices. This system revolutionizes traditional health monitoring practices by offering an automated, efficient, and accurate means of detecting and addressing potential health concerns in chickens. The system focuses on practicality and usability, assisting poultry farmers in maintaining optimal chicken health and mitigating disease outbreaks. The Chicken Health Detection System is envisioned as a valuable tool in poultry farming, aligning with industry demands for advanced monitoring solutions to ensure the welfare and productivity of chicken populations.

2.2 Project block diagram

In this project, The ESP32-Cam is a microcontroller board with a built-in camera module that captures images of chickens for health detection. Edge Impulse, a software platform, processes captured images and performs model inference to determine chicken health status. The Arduino microcontroller facilitates real-time transmission of health status classification results from Edge Impulse to ThingSpeak, an IoT platform that provides real-time monitoring and visualization of chicken health status. ThingSpeak enhances proactive management and prompts intervention for poultry health management, providing customizable dashboards, trend analysis, and alerting.

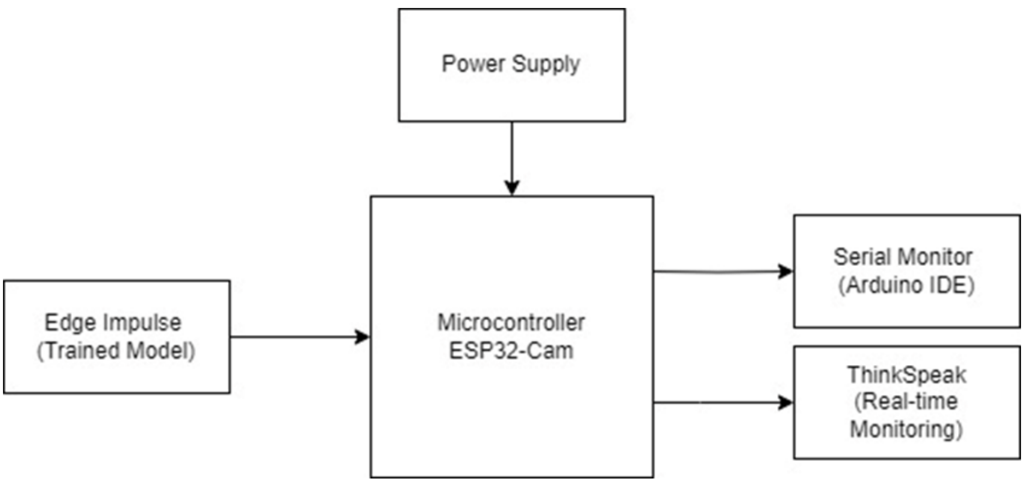


Fig 1 *Project Block Diagram*

2.2 Flowchart of the Project

The Chicken Health Detection System using Edge Impulse with ESP32-Cam is a comprehensive solution that integrates hardware and software components to achieve real-time monitoring and control of poultry farms. The ESP32-Cam serves as the primary platform for image capture, preprocessing, and real-time monitoring, capturing high-rate images suitable for continuous monitoring. Its integration with the Edge Impulse firmware enables object detection and classification tasks using captured images, essential for identifying and differentiating healthy and unhealthy chickens based on predefined health indicators. The software components include the Edge Impulse firmware, which provides a comprehensive machine learning platform for developing and deploying machine learning models. The firmware enables the creation of an impulse based on labeled data, allowing the system to recognize and classify various health conditions in the chickens. The impulse is exported to an Arduino library, which can be imported into the Arduino IDE for further testing and validation. Once the library is successfully imported, the system undergoes testing with the ESP32-Cam to verify its ability to detect unhealthy chickens in real time. The Chicken Health Detection System using Edge Impulse with ESP32-Cam has several benefits, including enhanced productivity, reduced costs, and improved animal welfare. By providing real-time monitoring and control, the system enables farmers to identify and address health issues promptly, reducing the risk of disease outbreaks and minimizing the need for antibiotics. Additionally, the system's machine learning capabilities enable it to learn and adapt to changing health conditions, making it a powerful tool for improving animal welfare and productivity.

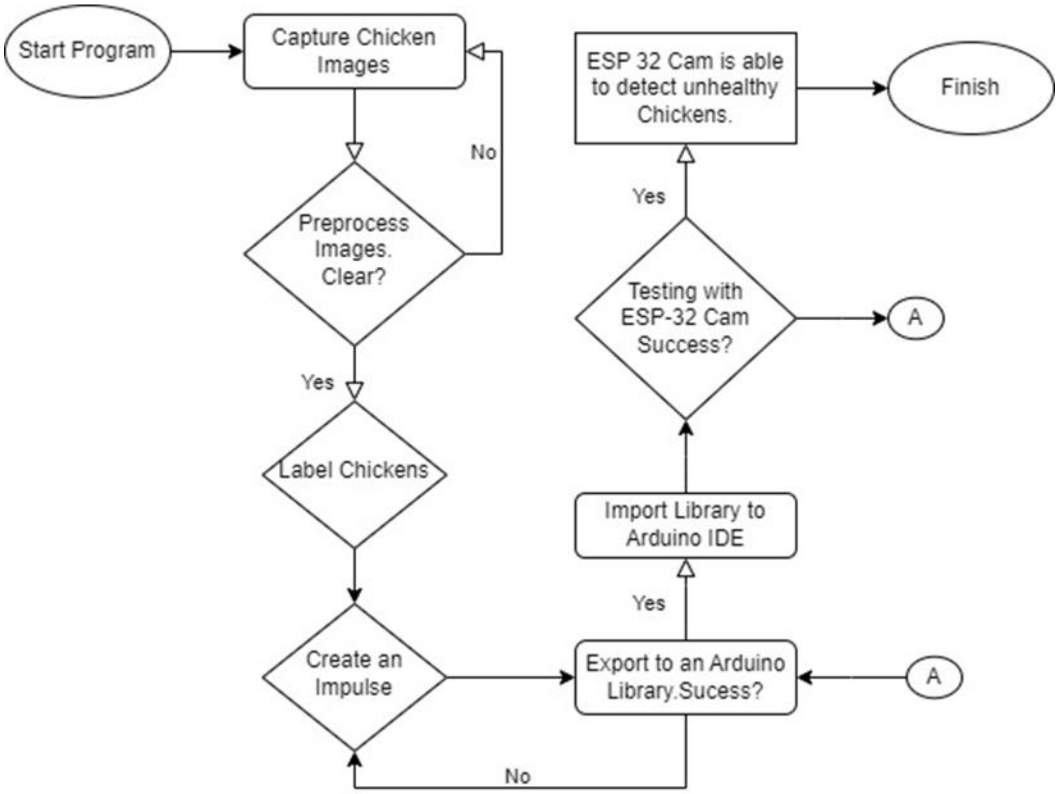


Fig 2 *Flowchart of the Project*

2.3 Pinout Diagram of ESP32-Cam

The ESP32-Cam module is a unified entity that combines the ESP32 microcontroller and the OV2640 camera sensor, simplifying the setup process and ensuring efficient communication. The camera sensor is directly embedded within the module, allowing users to focus on utilizing the module's combined capabilities without the need for intricate wiring or additional connections. The power supply component is crucial for providing voltage for the module, which can be powered through USB, battery, or external sources. This flexibility allows the module to be deployed in various scenarios, from indoor setups with USB power to outdoor installations requiring battery or external power sources. The simplified circuit diagram provides a clear overview of the system architecture.

Fig 3 *Pinout Diagram of ESP32-Cam*

3.0 Results and Discussion

The project aims to develop a Chicken Health Detection System using Edge Impulse and the ESP32-Cam to accurately identify healthy and unhealthy chickens in real time. The technology aims to handle diverse datasets encompassing various breeds, ages, and health conditions of chickens, demonstrating proficient real-time image classification to quickly identify and address health issues in poultry. The expected outcomes include developing an effective image classification system capable of handling diverse datasets, demonstrating proficient real-time image classification, and providing measurable accomplishments that contribute to the system's reliability and accuracy evaluation. The project also aims to establish a framework for future projects demonstrating the potential of machine learning and edge computing in improving poultry health monitoring and management practices. The results will highlight the strengths and limitations of the system, providing insights into its practical application and potential enhancements for broader adoption in poultry farming.

3.1 Design of the Prototype

The experimental setup involves the following key components. The system uses the ESP32-Cam to capture pictures of chickens, which are subsequently processed by Edge Impulse to train machine learning models for detecting the chicken's health status. The dataset utilised for this training consists of labelled pictures that identify healthy and unhealthy chickens, giving a firm basis for the model's learning and accuracy. ThinkSpeak software is used for real-time detection and monitoring, allowing for continuous analysis and fast reporting on the health of the chickens. This integration of hardware and software components results in a powerful, real-time health detection system that can assist poultry farmers in quickly identifying and managing any health issues. Instead of taking pictures straight out of a chicken coop, the camera is connected to a computer via a USB cable. Since it was impractical to access a chicken coop and handling the logistics of live animals would have been challenging, real chickens were not included in this demonstration. Instead, images were used to train and test the detection system, which was a simpler option. Because of the ESP32 Cam's effective picture capturing and processing capabilities, which enable real-time health detection of chickens without the need for constant human supervision, the device proves to be quite helpful in this project. Its wireless capabilities and compact size also make it perfect for deployment in a variety of environments, allowing for continuous data collection and analysis even in isolated or challenging-to-reach areas. The FOMO (Faster Objects, More Objects) model was chosen for this task due to its efficiency and accuracy in object detection and classification, particularly in scenarios where multiple objects need to be detected within an image. FOMO is designed to work well on edge devices with limited computational power, making it an ideal choice for real-time applications in agricultural settings. Additionally, FOMO's ability to quickly and accurately identify and classify multiple objects within a single image ensures that the health status of chickens can be monitored effectively and promptly. This capability is crucial for timely interventions and maintaining the overall health of the chicken.

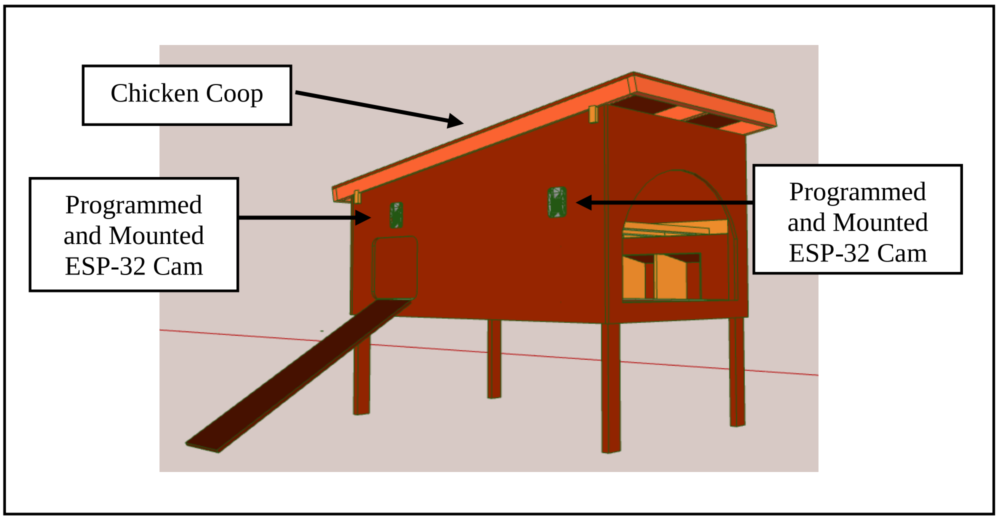


Fig 4 and 5 *Proposed Prototype and Experimental Setup of the Project*

3.2 Results of the project on Arduino IDE

The serial monitor output displays the real-time results of an ESP32-CAM running a machine learning model to detect chicken health status. Each line in the monitor starts with a timestamp, then the condition identified (either healthy or unhealthy chicken) and the confidence level of the detection. The confidence value reflects how certain the model is about its prediction, with values closer to one indicating greater accuracy. The output also gives bounding box coordinates (x, y, width, and height), which show the position and size of the detected object within the frame. When no item is discovered, the result reads "No objects found" or "-> 0". This data from the serial monitor is critical for visualizing the health status of chickens over time, which may be plotted using a platform such as ThingSpeak. In ThingSpeak, these confidence levels are shown on a graph, with peaks and valleys representing the detection of healthy and unhealthy chickens. This visualization helps in the real-time detection of the chicken's health, providing useful insights for prompt action. The serial monitor timestamps match the time data on the ThingSpeak graph, ensuring that detections are appropriately represented across time.

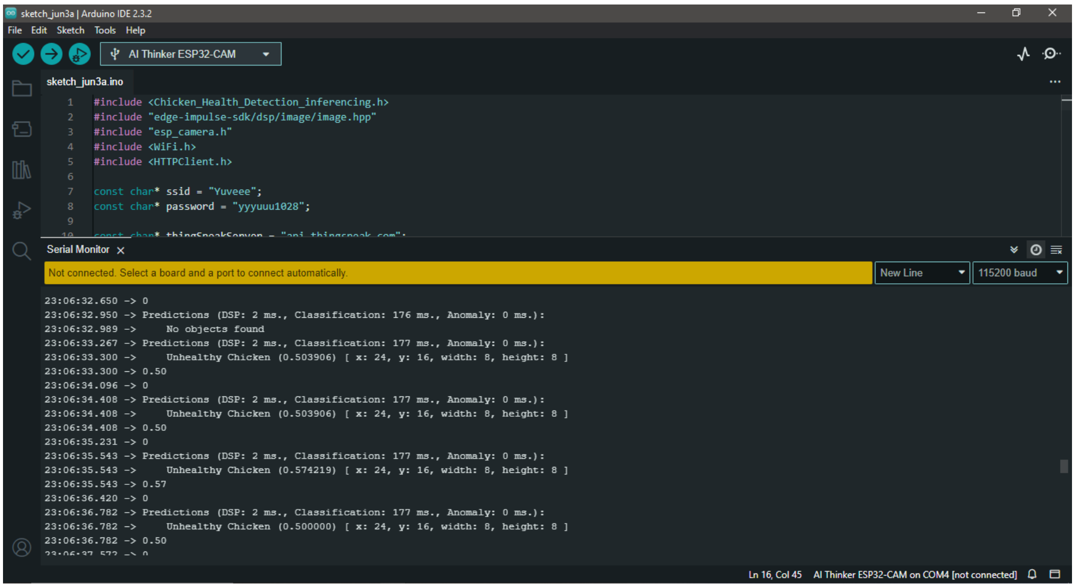
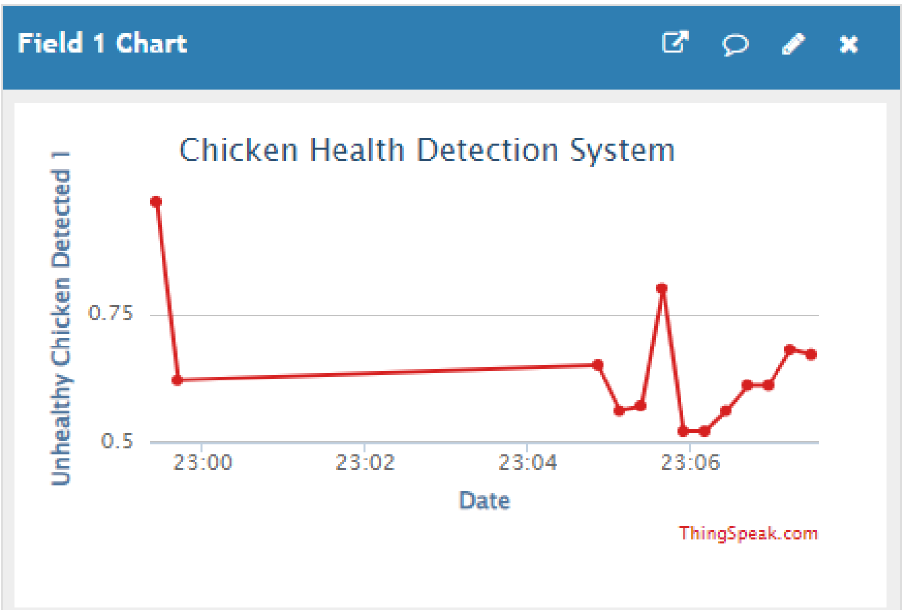


Fig 6 *Live view of the prototype from the WI-FI camera*

3.3 Results of the project on ThinkSpeak IDE

The ThingSpeak graph titled "Chicken Health Detection System" shows the confidence levels in detecting healthy and unhealthy chicken over a period of time. The y-axis indicates the confidence value, which ranges from 0.5 to 1, indicating the certainty of detection, and the x-axis represents time. Higher values on the y-axis indicate greater confidence in the detection of healthy and unhealthy chickens. The curve begins with high confidence levels near 0.75, indicating that the system correctly identified multiple unhealthy chickens. As time goes on, the confidence ratings fall, reaching as low as 0.5, implying that either no healthy or unhealthy chicken were found or the detections were less accurate. Around 23:06, there is a noticeable spike, indicating a high-confidence detection, followed by additional fluctuations. This graph demonstrates the dynamic nature of the chicken health detection system, since detections can vary considerably over short time periods. The graph provides a clear visual representation of detection trends and aids in determining circumstances of increased and decreased confidence in spotting healthy and unhealthy chicken.



Penerbit UTHM

Fig 7 *Live view of the prototype from the WI-FI camera*

3.4 Detection Test Results

The table captures a sequence of events recorded by an ESP32-CAM equipped with a machine learning model to monitor the health status of chickens. Each row corresponds to a specific timestamp, indicating when the detection occurred. The table lists the detected condition (either "Unhealthy Chicken" or "Healthy Chicken"), the confidence value of the detection, and the coordinates and dimensions of the bounding box surrounding the detected object. The confidence value, which ranges from 0 to 1, reflects the model's certainty regarding its prediction, with higher values indicating greater confidence. For example, at 00:59:47.695, an unhealthy chicken is detected with a high confidence value of 0.742188, and the bounding box is defined by the coordinates (24, 16) with a width and height of 16. This is followed by a subsequent confidence value of 0.74 at 00:59:47.895, but without a specific condition or bounding box, indicating a continued confidence level without a new detection. Similarly, at 00:59:55.521, a healthy chicken is detected with a confidence of 0.75, and the bounding box is smaller, reflecting the precise location and size of the detected chicken. As we move to the later timestamps, such as 23:06:32.989, the entry "No objects found" indicates that the system did not detect any chickens at that moment. However, shortly after, at 23:06:33.300, an unhealthy chicken is detected with a confidence of 0.503906, and the bounding box coordinates (24, 16) and dimensions (8, 8) suggest a smaller detection area. This pattern continues with consistent detections of unhealthy chickens with varying confidence values and bounding box dimensions, demonstrating the system's ability to monitor and classify the health status of chickens in real-time. The table effectively logs these detections, providing a clear timeline of events and the model's performance in detecting unhealthy chickens.

Table 2 *Functionality of the pushbuttons*

Timestamp	Condition	Confidence Value	Bounding Box (x, y, width, height)
00:59:47.695	Unhealthy Chicken	0.742188	(24, 16, 16, 16)
00:59:47.895	-	0.74	-
00:59:55.521	Healthy Chicken	0.750000	(8, 24, 8, 8)
00:59:55.562	-	0.75	-
00:59:56.352	Unhealthy Chicken	0.652344	(16, 24, 8, 8)
00:59:57.268	-	0	-
00:59:57.316	Unhealthy Chicken	0.761719	(32, 32, 8, 8)
00:59:58.562	Unhealthy Chicken	0.628906	(8, 8, 8, 8)
00:59:59.236	-	0.63	-
00:59:59.565	Unhealthy Chicken	0.644531	(32, 8, 8, 8)
00:59:59.565	-	0.64	-
23:06:32.950	-	0	-
23:06:32.989	No objects found	-	-
23:06:33.300	Unhealthy Chicken	0.503906	(24, 16, 8, 8)
23:06:34.408	Unhealthy Chicken	0.503906	(24, 16, 8, 8)
23:06:35.543	Unhealthy Chicken	0.574219	(24, 16, 8, 8)
23:06:36.782	Unhealthy Chicken	0.500000	(24, 16, 8, 8)

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3.5 Discussion on Results

The development and implementation of the Chicken Health Detection System established the potential of edge computing and machine learning for real-time chicken health detection. The integration of the ESP32-CAM with the Edge Impulse platform allowed for efficient image collection and classification, resulting in precise detection of healthy and unhealthy chicken. The deployment process using the Arduino IDE, followed by real-time data display on ThingSpeak, demonstrated the system's practicality and effectiveness. The ability to transmit classification data wirelessly for remote monitoring is a huge step forward, allowing farmers to respond quickly to any health issues, increasing overall chicken management and welfare. The detection system produced promising results, with the system correctly categorizing chicken health states. The use of labeled datasets for training the machine learning model on Edge Impulse assured that the system would cope with changes in chicken breeds, ages, and health problems. The real-time detection capabilities, proven by both the serial monitor on the Arduino IDE and the visualizations on the ThingSpeak platform, provided useful information. This continual monitoring is critical for early detection of health issues, which could reduce death rates and increase productivity in chicken farming operations. However, there is potential for further enhancement. The system's performance could be improved further by expanding the dataset to include more diverse images and settings, hence increasing the model's consistency. Furthermore, enhancing the ESP32-CAM's power consumption and connection would improve system efficiency and reliability in a variety of farming scenarios. Future studies could potentially look into adding more sensors to collect more comprehensive health data, hence expanding the capabilities of this edge-based health detection system. Overall, this study establishes a solid platform for utilizing technology to improve chicken health management, leading the way for more advanced agricultural applications.

3.6 Achievement on Objectives

The objectives of this study were thoroughly studied and successfully achieved, providing an outline for future developments in poultry health detection. First, a wide variety of chicken images representing various ages, breeds, and health types was gathered. This dataset serves as the foundation for training the machine learning model, which can accurately classify chicken health conditions in real time. The dataset's accurate labeling and preparation ensures that the model is able and capable of managing the various circumstances found in practical chicken raising environments. Secondly, the accomplishment of the research goals was made possible by the effective integration of the ESP32-Cam for real-time data collecting and processing. The ESP32-Cam's edge data collection and processing capabilities offered what was required for the prompt detection of possible health abnormalities in chicken populations. This connection made it easier for physical components to communicate with one another and made it easier to put the machine learning model that was created with Edge Impulse into use. By accomplishing these goals, the study shows that using IoT technology for chicken health detection is both feasible and practical, creating opportunities for the poultry sector to adopt more advanced and effective management techniques.

4.0 Conclusion

The final outcome of this research journey is the Chicken Health Detection System, which serves as a beacon of innovation in the poultry farming industry. This system provides an unique solution for real-time monitoring of chicken health by strategically combining IoT technologies and machine learning techniques. By seamlessly integrating Edge Impulse and the ESP32-Cam, it not only improves welfare standards but also emphasizes the transformative potential of technology in agriculture. However, as we reflect on its accomplishments, it becomes clear that the journey toward sustainable and efficient poultry management is advancing, requiring constant refinement and adaptation to address developing issues. The development and implementation of the Chicken Health Detection System are important turning points in the effort to modernize chicken farming operations. The system demonstrates the potential of using technology to handle complex agricultural challenges by successfully completing the objectives of this study, which included dataset collection, preparation, and hardware integration. Its capacity to deliver timely insights into chicken well-being highlights its potential to transform existing monitoring approaches, promoting higher welfare standards and productivity in the poultry business. Looking ahead, the development of the Chicken Health Detection System signifies the start of a new era in poultry management, not the end of the journey. Strategic proposals for further improvement, such as increasing the dataset, improving hardware components, and investigating advanced machine learning approaches, pave the way for future innovation in this field. By embracing these principles and cultivating a culture of collaboration and experimentation, we may realize technology's full potential for improving poultry welfare, sustainability, and profitability.

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