AUTOMATED RICE FIELD PROTECTION SYSTEM FROM BIRDS USING MACHINE LEARNING WITH SMS ALERT

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ABSTRACT. Birds pose a significant threat to agriculture, particularly in rice fields. The most common pest birds in the Philippines include Lonchura atricapilla (Maya), Egret (Tagak/Tulabong), Dove, and Sparrow (Goryon). Traditional bird deterrent methods such as scarecrows, hawk kites, colored lights, lasers, and noise-based solutions have proven ineffective in recent years. This study presents an Automated Rice Field Protection System from Birds using Machine Learning with SMS Alerts, which utilizes a Raspberry Pi 4, a camera module, and a speaker to detect birds and trigger deterrent actions. The bird detection model was trained using YOLOv8 on Roboflow, leveraging Convolutional Neural Networks (CNNs) for feature extraction and real-time detection. The system is implemented using Python, with OpenCV for image processing and TensorFlow Lite for lightweight inference. When a bird is detected, an SMS alert is sent to the farmer, and a repellent sound is played to deter birds. The proposed system achieved an accuracy of 90%, demonstrating its effectiveness in reducing bird intrusions in rice fields. This cost-effective and automated approach provides a modern alternative to traditional bird deterrent techniques. Future recommendations include improving model accuracy with more training data, integrating additional sensors, and expanding the system for broader agricultural applications.

208 words

Keywords: *Birds, Machine learning, SMS alert, Rice field protection system, YOLOv8, Raspberry pi, Roboflow, CNN*

1. INTRODUCTION

Rice equals life for millions of people, and it is planted in many regions of the world. The Philippines continues to work on modernizing and strengthening its agriculture sector, both the government and private sectors encourage advanced technology and smart farming techniques in ways to increase harvests and minimize losses [1]. Bird damage is a persistent issue for many Filipino rice farmers and can occasionally be a serious problem in certain areas, even though the country's losses remain unclear due to unavailability of any detection and protection system in the rice fields [2].

Machine Learning can be highly applied in identification in crops based on site images. [4] The identification of the type and number of insects becomes a vital aspect for crop protection and yield conservation since most of the farmers live away from their farms due to the factor of distance and heavy cost over appointing labor for the same kind of purpose, that’s why constant monitoring of the fields is impossible.

In the past, computer vision has been used in numerous studies to detect disease in the vegetative stage by [5], but very few included birds and virtually none included real-time alert systems. More importantly, at present, most of the solutions are not scalable and are very expensive for small-scale farmers.

This study aims to bridge the gap between the utilization of emerging technologies and their real-world applications. Specifically, it focuses on designing and developing an economical and functional bird detection system that leverages computer vision techniques and machine learning methods. The system uses a Convolutional Neural Network (CNN), specifically YOLOv8, trained and validated for bird detection, and implements it using TensorFlow Lite to detect birds in rice fields captured by a camera. One of the primary objectives of this project is to combat pests, specifically birds, and to contribute to innovation in the agricultural industry.

2. OBJECTIVES OF THE STUDY

This study is primarily done to design a rice field protection system for birds with bird detection using Machine Learning models and SMS alerts that will notify the farmers. The specific objectives are:

1. To design a machine learning model that can detect and identify birds in the rice field.
2. To develop an automated alarm system that will deter a bird when it is detected, which minimizes the labor and manual work for farmers in protecting their rice crop from birds.
3. To test the accuracy and effectiveness of the system in terms of bird detection and identification, and evaluate the effectiveness of SMS alerts to inform the farmers about the bird intrusion.

3. METHODS

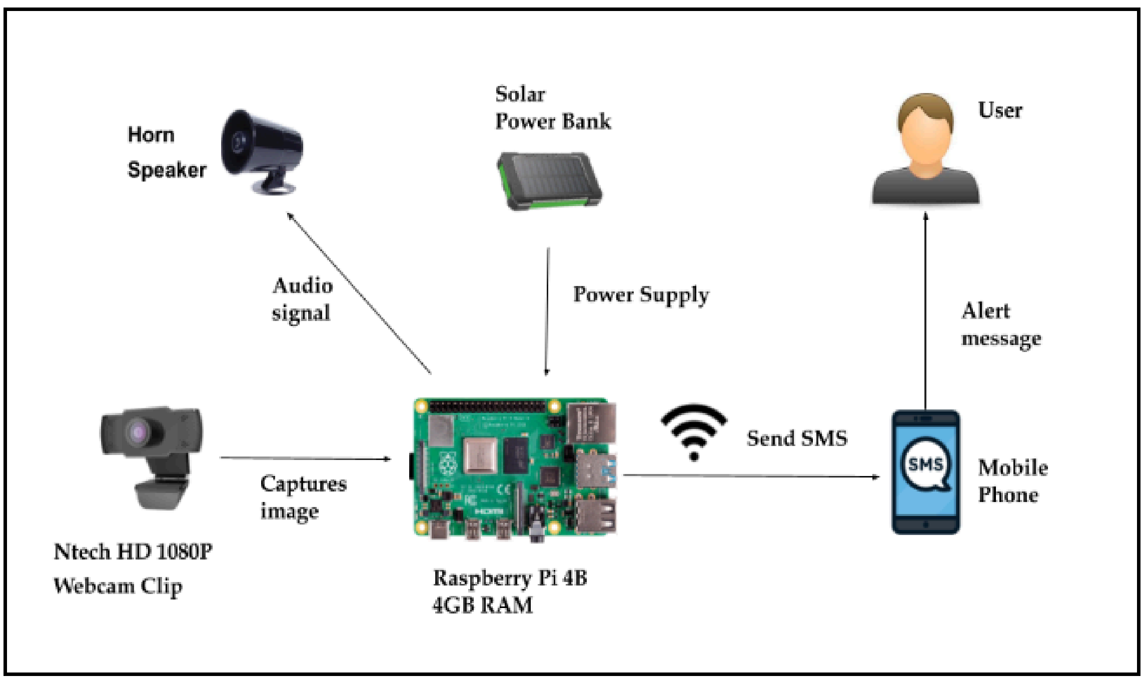

Figure 2. Conceptual Diagram

The diagram shows a visual representation of how each component interacts within the system. The Camera will send the captured data to Raspberry Pi 4 Model B for bird detection analysis, then the Raspberry pi will process the data using machine learning algorithms to detect birds. When birds are detected, the Raspberry Pi will initiate a dual-alert system that sends an alert message to designated mobile phones to farmers and audio alerts through the speaker. Mobile phone users receive alerts and can take immediate actions to mitigate bird damage in the rice fields.

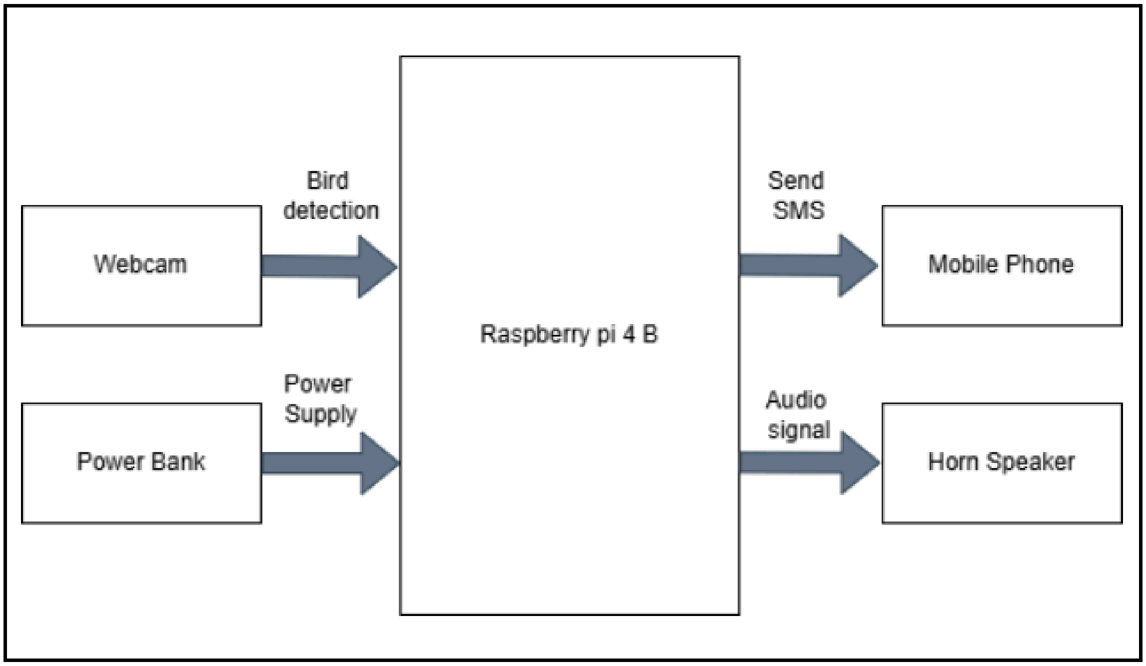

Figure 3. Process Block Diagram

The Block diagram visually represents the major components of the system, including RaspberryPi 4 Model B, Webcam, Horn Speaker and Power Bank. Each block indicates the function of the component, such as image capture, processing, and alert generation, along with arrows showing the flow

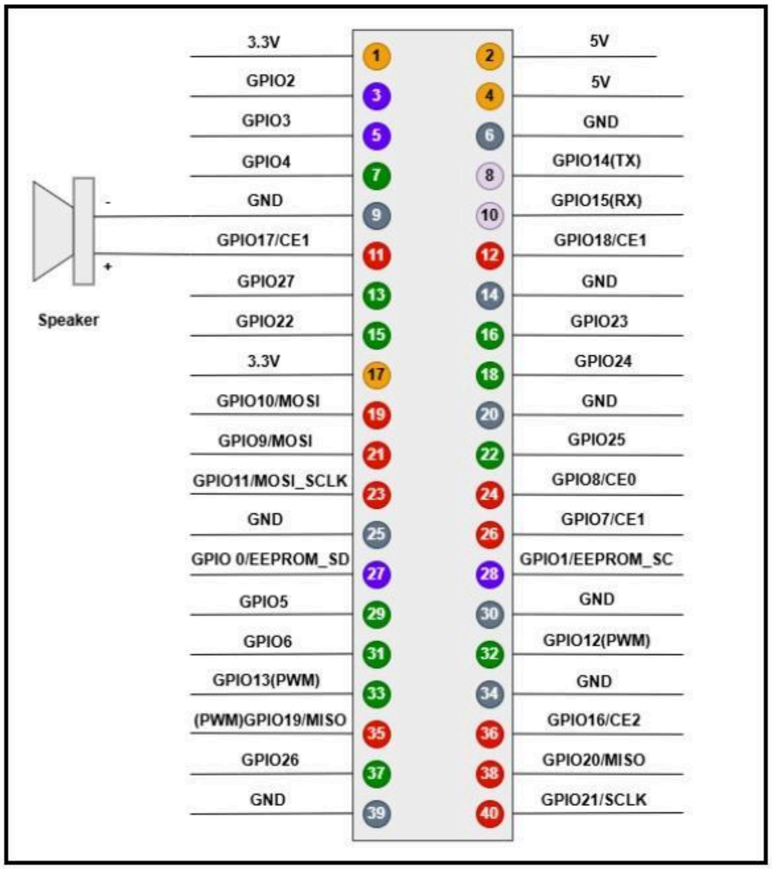

Figure 4. Schematic Diagram

The schematic diagram is an accurately depicted outline of the electrical connections and components of the board. It is the wiring between the Raspberry Pi and the speaker.

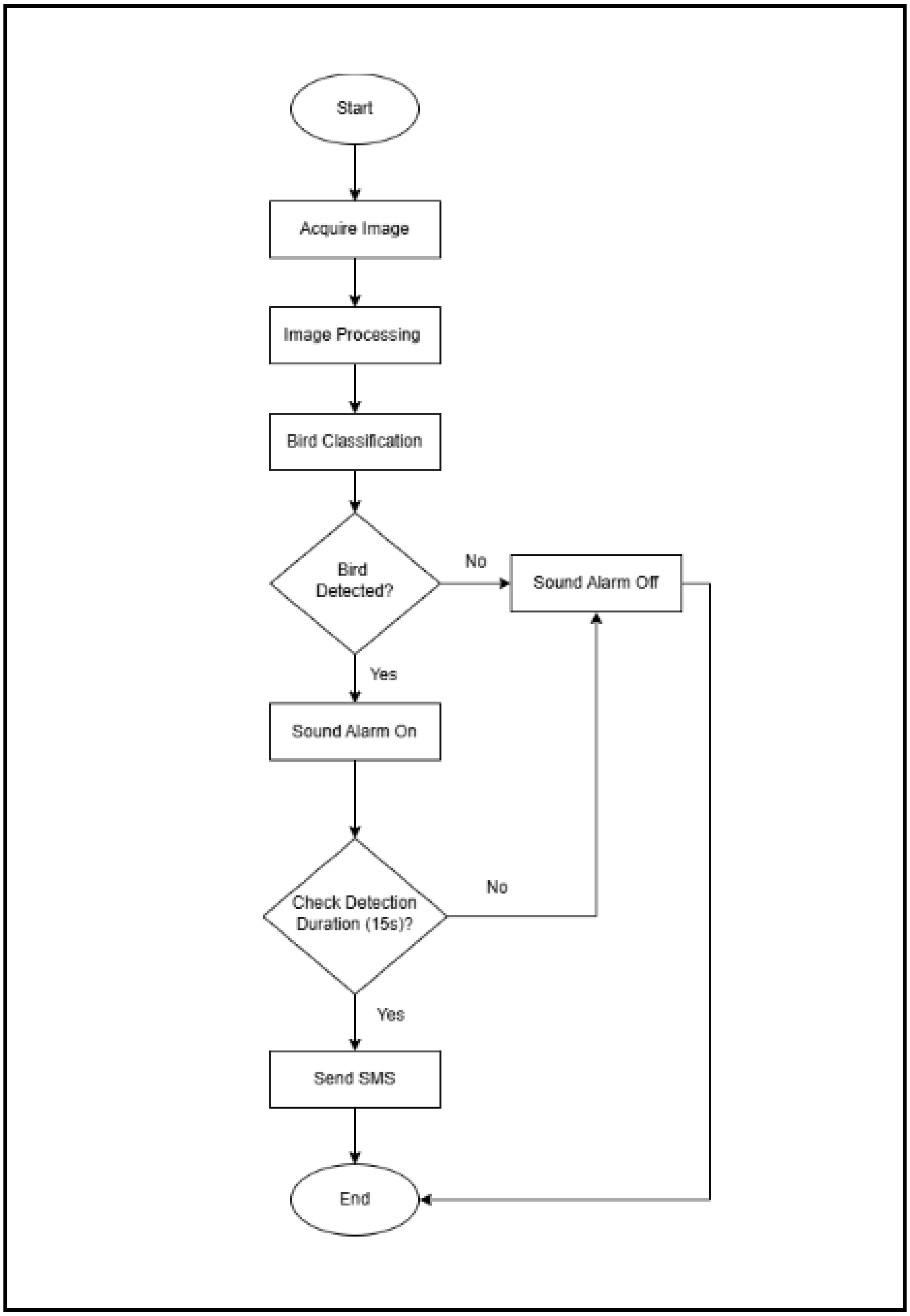

Figure 5. Flowchart of the proposed system

The system flowchart illustrates the step-by-step process that the rice field protection system follows. It starts with camera capturing of the rice field, proceeds to the machine learning model analyzing those images for bird detection and outlines the decision making process to send a SMS alert to farmers. The flowchart emphasizes key decision points, such as whether a bird is detected, and outlines the result action, such as sending an SMS or activating the speaker as a sound alarm.

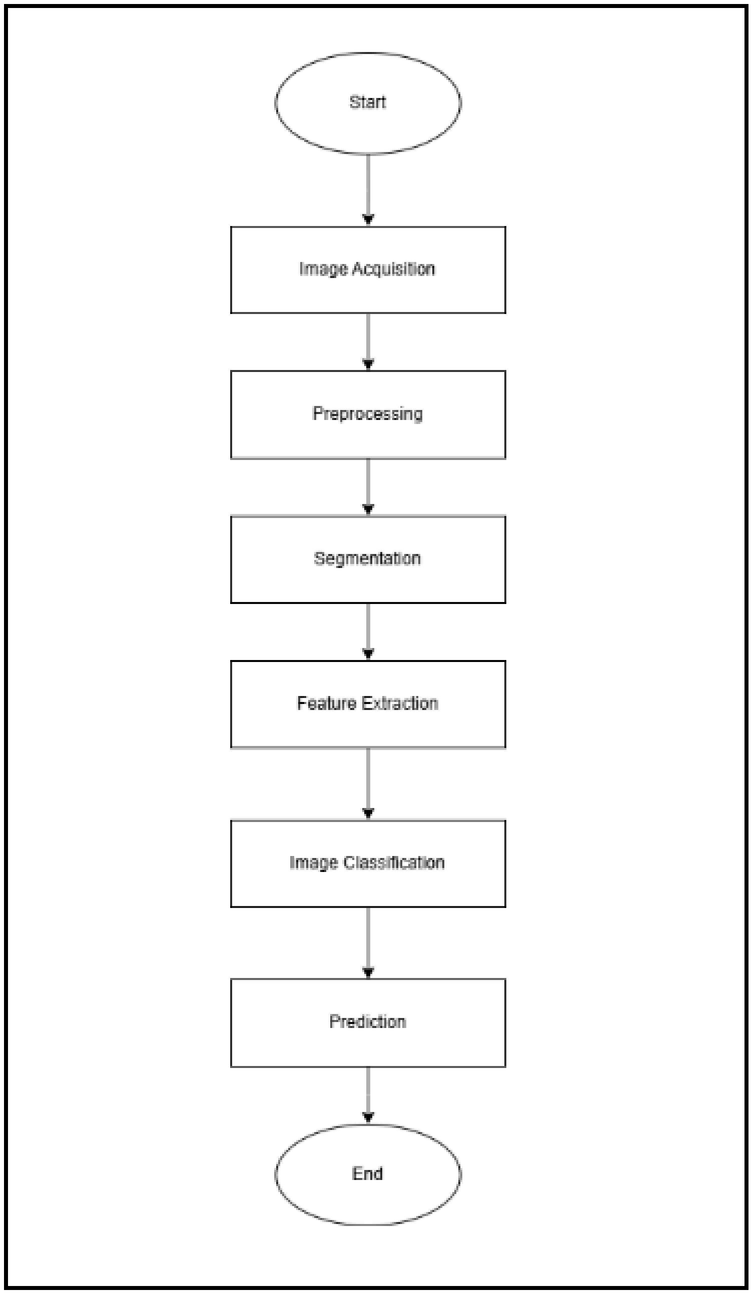

Figure 6. Image Processing Flow

The image processing begins with image acquisition of the rice field, which is then passed to a Raspberry Pi 4 Model B for further processing. The captured image undergoes pre-processing, including resizing to 640×640 and auto-orientation. The processed image is then fed into a custom object detection model trained using YOLOv8 in Roboflow. The dataset consists of images from both the COCO dataset and a custom dataset. The trained models are optimized and exported as TensorFlow Lite models for efficient inference on Raspberry Pi. OpenCV is used for image processing, while TensorFlow Lite ensures fast and lightweight detection and classification of birds in real time.

4. RESULTS AND DISCUSSION

System Operation

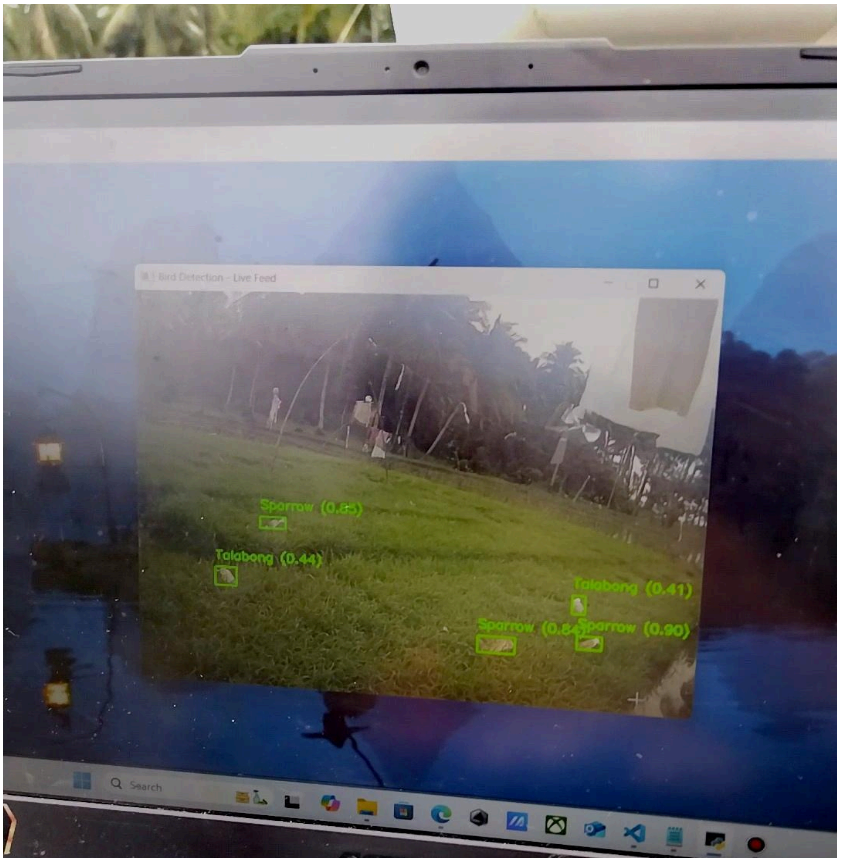

Figure 17. Live Camera Bird Detection

Initial tests demonstrate promising results in effectively identifying birds and triggering alarms. The integration of machine learning allows for high detection accuracy, reducing false positives. The automated SMS alerts provide real-time notifications, ensuring farmers can take immediate action if necessary. Environmental adaptability tests confirm that the system remains functional in various weather conditions. Further refinements are being considered to improve the system's efficiency and reduce power consumption.

Alert System

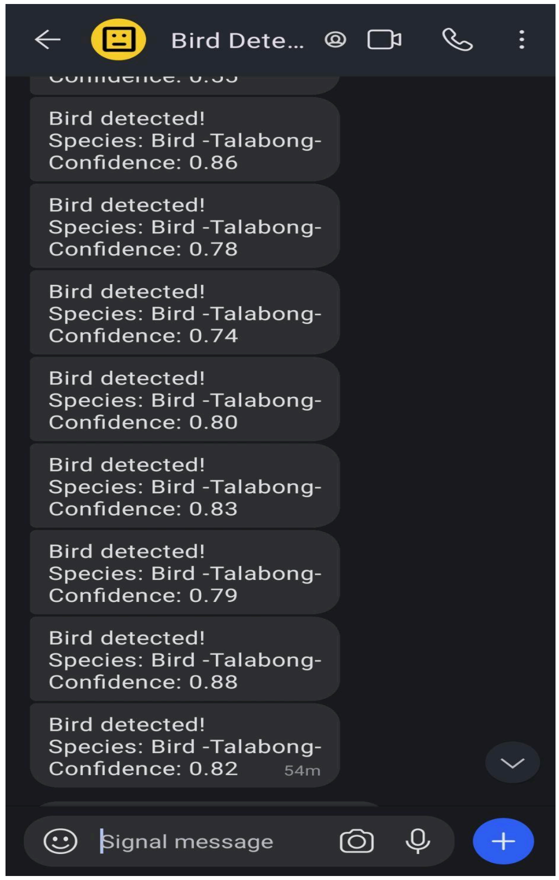

Figure 19. SMS Notification

To notify users of the detection, the system uses a third-party app called Signal. There is a 15-second delay before the system initiates an automated procedure that sends an SMS to the designated mobile device. This immediately notifies users, giving them insight into the birds' activities and allowing them to take prompt action to prevent potential harm to property or crops.

Table 2.
Precision, Recall, F1-Score

Class	Precision	Recall	F1-Score	Support
Tulabong	0.87	0.88	0.87	500
Red Maya	0.87	0.85	0.88	500
Dove	0.85	0.86	0.85	500
Sparrow	0.86	0.87	0.87	500

The table presents the evaluation metrics (Precision, Recall, and F1-Score) along with Support for each class. Precision measures the accuracy of positive predictions, Recall indicates the model's ability to correctly identify all relevant instances, and F1-Score provides a balance between Precision and Recall. Support represents the total number of test images per class, ensuring a fair evaluation of the model's performance across classes.

Table 3.
Bird Type Identification

Test No.	Bird Detected (Yes/No)	Bird Type	Confidence (%)
1	Yes	Tulabong	88%
2	Yes	Red Maya	87%
3	Yes	Dove	86%
4	Yes	Sparrow	90%

Based on the model's confidence scores, this table provides insight into the system's accuracy in identifying various bird species as well as the dependability of its predictions.

Table 4.
Bird Detection Alarm - Performance Metrics

Metric	Value
Precision	0.84
Recall	0.85
F1-Score	0.84
Accuracy	0.84

The bird detection alarm system demonstrates solid performance, with a precision of 0.84, meaning 84% of the times the alarm is triggered, it accurately detects a bird. The recall is 0.85, indicating that the system successfully identifies 85% of the birds present in the dataset. The F1-score, which balances precision and recall, is 0.87, showing a good overall detection capability. The accuracy stands at 0.87, meaning it correctly identifies and makes the birds go away.

Table 5.
SMS Alert Test Table

Test No.	Bird Detection Status	SMS Sent (Yes/No)	Time Taken to Send SMS (seconds)
1	Bird Detected	Yes	15.6
2	No Bird Detected	No	N/A
3	Bird Detected	Yes	16.8
4	Bird Detected	Yes	15.3

An SMS was successfully sent, with times ranging from 15.3 to 16.8 seconds and depending on the connection. In contrast, when no bird was detected, no SMS was sent, and the time is marked as N/A. This table helps assess the responsiveness and accuracy of the alert system, showing that the SMS is triggered correctly when a bird is detected, and no false alarms are sent when no bird is present.

5. CONCLUSION

The Automated Rice Field Protection System from Birds using Machine Learning with SMS Alerts successfully detects and classifies birds in rice fields, achieving 90% accuracy. By utilizing YOLOv8 trained on Roboflow, the system effectively identifies birds in real time, triggering a deterrent mechanism through repellent sound playback and SMS alerts. This modern, cost-effective, and automated solution offers farmers a more efficient alternative to traditional bird control methods. The results demonstrate that integrating machine learning with IoT-based automation can significantly improve crop protection and reduce agricultural losses.

6. RECOMMENDATION

System refinement suggestions from the researchers are the following:

- Enhance Model Accuracy by Increasing training data diversity, apply data augmentation, use higher resolution images for more accurate detection.
- Enhance Detection Capabilities with the addition of extra sensors like ultrasonic motion detectors, infrared cameras, or sound recognition to improve detection in different conditions.
- Expand System Application toAdapt the system for other crops, develop a mobile dashboard for real-time monitoring, and explore selective deterrence for different bird species.

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