Received: 28 JUN 2025 | Accepted: 30 NOV 2025 | Published Online: 30 NOV 2025
Recoletos Multidisciplinary Research Journal Vol. 13 no. 2Si (November 2025)
DOI: https://doi.org/10.32871/rmrj1302si.i2503

Original Article

Avian Pro: Intelligent Robot for Philippine Sparrow Detection and Deterrence using Laser Pointer

Mae Garcillanosa[1*], Jennifer Dela Cruz[2], Carl Mariz Bathan[1], Carlos Lyan De Guzman[1], Ryan Christian Vidal[1]

[1] Electronics Engineering, Mapúa Malayan Colleges Laguna, Cabuyao City, Philippines

[2] School of Electrical, Electronics, and Computer Engineering, Mapúa University, Manila, Philippines

*Correspondence: mmgarcillanosa@mcl.edu.ph

Abstract

Background: *Bird pests, particularly the Philippine Sparrow, pose a persistent threat to farmers in Luzon's southern and northern regions. Conventional deterrents such as scarecrows and lethal methods are often ineffective, unsustainable, and harmful to the environment.*

Methods: *This study developed an eco-friendly bird deterrent system using a Raspberry Pi microcomputer, image processing, and machine learning to detect and target the Philippine Maya. A green laser pointer, controlled by servo motors, was used as a non-lethal deterrent, activating only upon detection of pests.*

Results: *The system demonstrated effective bird detection within a range of 10 to 11 meters. Environmental factors, including sunlight and the prototype's positioning, influenced detection accuracy and laser performance. The system operated in short bursts of 10–15 minutes within a 2-hour window to conserve energy.*

Conclusion: *With its low-power design and potential for solar integration, the system provides a sustainable and environmentally friendly solution for managing bird pests in agricultural fields. It presents a viable alternative to traditional methods, promoting eco-conscious farming practices.*

Keywords

Philippine sparrow, pest management, sustainable agriculture, laser, intelligent robot, machine learning

INTRODUCTION

Rice production plays a significant role in the Philippines' agricultural economy. Since the 1960s, rice (locally known as palay) has been one of the most dominant crops in the Philippines, alongside corn, coconut, sugarcane, and bananas. This long-standing prominence highlights the critical role of rice in the country's agricultural landscape and food security (Briones, 2021). Additionally, according to the Philippine Statistics Authority (PSA), the country relies heavily on rice as a staple food, and its cultivation is crucial for ensuring food security and economic stability (Philippine Statistics Authority, 2019). However, rice fields in the Philippines face numerous challenges, particularly from pest infestations, which can severely affect crop yields. One of the most prevalent pests is the Philippine Sparrow (*Passer montanus*), also known locally as “Maya”, which damages rice crops by feeding on the grains, resulting in reduced productivity and financial losses for farmers (Philippine Rice Research Institute, 2021). Bird damage is a chronic problem for many Filipino rice farmers and can sometimes be a severe issue within localized areas. Three species of Philippine weavers (*Lonchura malacca, Lonchura leucogaster,* and *Lonchura punctulata*) are common pests, and other birds such as sparrows, parrots, and even ducks contribute to crop losses (Philippine Rice Research Institute, 2021).

Current methods for managing these bird pests primarily involve traditional techniques, such as using scarecrows or directly killing the birds, which are not only ineffective in the long term but also environmentally harmful. These methods often fail to address the root cause of the problem and can lead to an unsustainable cycle of pest control (Ramadhani & Priyambodo, 2024). Considering these issues, there is a growing need for more effective, sustainable, and innovative solutions to protect rice crops from bird pests without harming the environment or the ecosystem. Some of the technology-related approaches for bird management include visual frightening devices, such as effigies with movement, designed to scare birds by mimicking scarecrows. However, their effectiveness diminishes as birds habituate to the movement over time (Vantassel et al., 2015). Electrical fences, which act as sensors to detect and prevent bird pests from staying in fields, offer a more reliable solution, especially during peak bird migration seasons, as they can block large areas and respond to bird activity (Dyck & Warbick, 2017). Additionally, IoT systems using passive infrared sensors (PIR) and repellers with sound and light (Dela Cruz et al., 2020) have proven effective in repelling birds, with a reported 91.93% accuracy in preventing crop damage (Phetyawa et al., 2022). Laser pointers have also shown a high success rate, reducing bird presence by 97.8% in tested areas (Elbers & Gonzales, 2021), demonstrating their potential for non-lethal and sustainable pest control.

While previous studies have explored various methods for pest control in agriculture, a significant gap remains in addressing the specific challenge of bird pests in rice farming, particularly the Philippine sparrow. Traditional approaches such as scarecrows, netting, and bird culling are widely used but often prove ineffective over time and lack sustainability. Although some research has investigated automated pest detection systems, these typically focus on general pest management or employ deterrents like sound, drones, or motion-based repellers, which are not optimized for the unique behavioral patterns of bird pests in rice fields. Moreover, there is limited research—especially in the Philippine context—on integrating low-power, non-lethal deterrents such as laser pointers with advanced technologies like machine learning and image processing.

This study presents the first implementation of a low-power, machine learning-based, solar-integrated robotic deterrent system designed explicitly for smallholder rice farms in the Philippines. Unlike prior systems, it combines real-time image recognition with targeted laser-based deterrence to address endemic bird species such as the Philippine sparrow. By tailoring the system to local agricultural conditions and pest behavior, this research offers a novel, eco-friendly, and energy-efficient solution to bird pest management in rice farming.

Specifically, our study aims to develop a hardware system that is adaptable to the agricultural environment and capable of detecting bird pests, specifically the Philippine sparrow (Maya), using image classification. The system will utilize a laser pointer to deter these pests non-lethally, addressing the gap in current pest control methods that rely on traditional and unsustainable approaches. By integrating image processing and machine learning, the robot will not only identify bird pests with greater accuracy but also provide a more sustainable solution that minimizes environmental impact and reduces reliance on harmful chemicals or invasive techniques. This approach focuses on enhancing pest management practices in a way that promotes long-term sustainability for Philippine rice farmers.

METHODS

Hardware implementation

The detection and tracking components of the system are depicted in Figs: 1a and 1 b. The first component is the detection system section, which includes a webcam that produces a live video stream, which the Raspberry Pi 4 microcomputer uses as input. The Raspberry Pi serves as the core board, whose purpose is to implement image processing. The data captured by the camera from the rice field will be sent to the Raspberry Pi. The Raspberry Pi's CPU is freed up to handle the computationally demanding requirements of running machine learning models by connecting the Coral USB Accelerator, as seen in the figure. Enabling the system to identify objects more quickly, particularly in situations involving real-time scenarios. The researchers achieved a 16-23 fps increase when utilizing the Coral USB accelerator, compared to a 1-2 fps increase when it was not connected. Subsequently, the Arduino microcontroller will receive the location of the identified bird pest via serial communication sent by the Raspberry Pi.

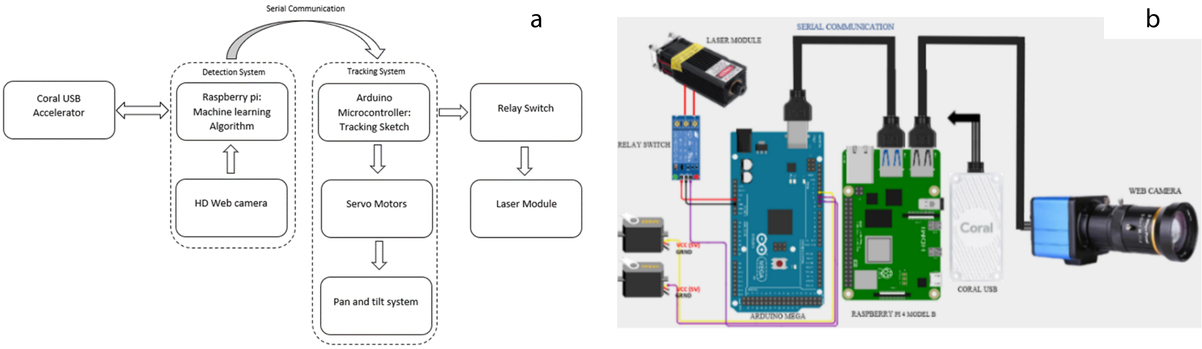

Figure 1. *(a) Block Diagram of the Proposed Hardware; (b) Representation of the Hardware Connectivity*

The comprehensive connection layout of the system, detailing the wiring of the relay and servo motors to the Arduino microcontroller, as well as the serial communication link between the Raspberry Pi and the Arduino, is shown in Fig. 2. Additionally, it showcases the hardware connections of the Coral USB accelerator and camera module to the Raspberry Pi.

Fig. 2 presents the entire power supply setup for the system, emphasizing the solar configuration's adequacy to sustain the system's operation for approximately 1.5 hours (40-90 minutes) during periods of no sunlight harvest, while also ensuring continuous operation in the presence of sunlight. It illustrates the essential components and connections required to establish a solar setup, ensuring the system's sustained power supply. Considering that the system operates at a maximum current of 30 watts, the solar setup is well-equipped to meet its power needs.

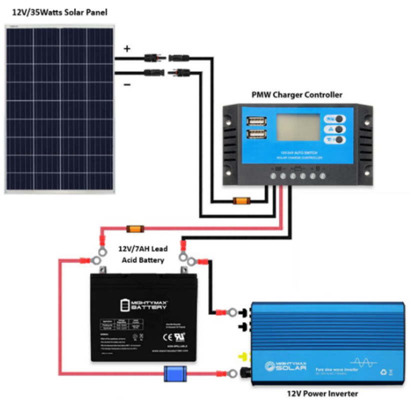

Figure 2. *Representation of Power Source Connectivity*

System overview

As seen in Fig. 3, the procedure for identifying and categorizing bird pests in rice fields is integrated into the object recognition process utilizing a Convolutional Neural Network. Initially, the system activates the web camera and begins acquiring a real-time video feed, generating frames at a rate of 23 frames per second. Upon receiving a video input featuring a bird for testing, the system conducts feature extraction through its convolutional layers, reducing data dimensions and yielding a more concise dataset. Subsequently, the system returns coordinates to establish bounding boxes.

If the system identifies the primary subject as something other than a bird pest, it continues the detection process until a bird pest is detected. Conversely, suppose the system identifies the primary subject as a bird pest. In that case, it calculates the object's position within the frame, prompting the servo to move and adjust the camera to center on the object's position. It then activates the laser pointer to deter bird pests.

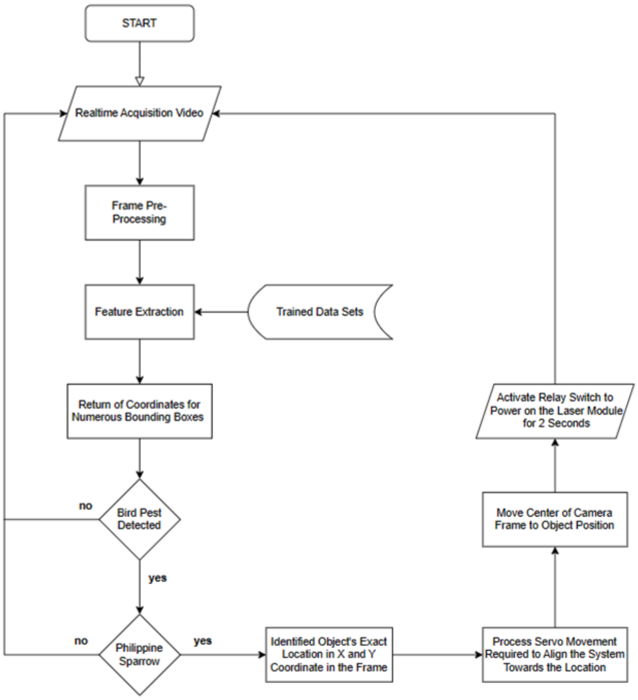

Figure 3. *System Process Flow*

Training the model

This study will utilize the stereoscopic method for image capture, employing a single camera to detect birds based on their identification and movements. The detection range is limited to a maximum of 45 meters. The system's implementation will be based on pixel calculations aligned with the camera's target specifications to ensure accurate detection (Notla et al., 2022).

The dataset used in this research was developed by collecting images of bird pests in rice fields, as well as isolated images of birds, to train a machine learning model for classification purposes. A total of 1,800 images were compiled, consisting of 800 images of bird pests and 1,000 images showing bird pests within actual rice field environments. The dataset includes variations in bird pest sizes to improve the model's robustness in detecting targets from long distances. However, it is important to note that the sample size is relatively small for deep learning applications, which may increase the risk of overfitting and limit generalization to unseen data. To mitigate these risks, dimensionality reduction techniques such as feature selection and feature extraction were applied. Future work may involve expanding the dataset and incorporating data augmentation strategies to enhance model performance and reliability.

After gathering all the images for the dataset, the next step involves annotation, where the images are marked to indicate the location and appearance of the pests. The researchers have opted to use an open-source tool called LabelImg, as shown in Fig. 4. This Python-based tool enables graphical annotation of each image in the dataset. Bounding boxes are drawn around the bird pests to identify and label them for the machine learning model accurately.

Once annotated, LabelImg saves the annotations in XML files using the Pascal VOC format. These XML files are then converted into TFRecord files, a format suitable for training the machine learning model. This conversion facilitates efficient data handling during the training process.

Figure 4. *Labeling User Interface (UI)*

The researcher chose IBM Watson Visual Recognition API for image classification using Convolutional Neural Networks (CNN), which provides enhanced graphical distinctions among bird species, allowing the system to identify them more accurately. This approach aligns with findings reported by Mahmood et al. (2022) and Jasim et al. (2022). In this case, IBM Watson Visual Recognition API is a highly cognitive algorithm that is well-suited for visual recognition. Patterns in the collected data are used to process and interpret visual information, enabling the system to make predictions based solely on image inputs. This means the model can effectively classify and respond to bird pest activity without requiring additional sensor data, relying entirely on visual cues extracted from the images (Zahra EL Bouni et al., 2021).

The CNN model was trained using a standard architecture comprising multiple convolutional layers, followed by pooling layers and fully connected layers. The training process consisted of 50 epochs, with a learning rate of 0.001, optimized using the Adam optimizer. The dataset was split into two sets using an 80:20 ratio, with 80% of the images used for training and 20% reserved for validation and testing. This split ensured that the model was exposed to a diverse set of examples while maintaining a separate set for unbiased performance evaluation.

To evaluate the effectiveness of the trained model, several performance metrics were monitored throughout the training and testing phases. These included accuracy, precision, and recall, which provided insights into the model's ability to correctly classify bird pests and minimize false positives and false negatives. Accuracy measured the overall correctness of predictions, while precision assessed the proportion of accurate identifications among all optimistic predictions. Recall, on the other hand, indicated the model's ability to detect actual bird pests present in the images. These metrics were essential in validating the model's reliability and guiding further optimization efforts. Future iterations may also incorporate F1-score and confusion matrix analysis to gain deeper insights into classification performance.

Prototype set-up

Fig. 5 shows the system along with its components positioned inside. The setup includes an RPi (Raspberry Pi), Arduino, solar setup, and Coral USB devices. The system is situated on the side of the rice field, with a camera capturing in-depth information and images within the field. The camera features an 8-megapixel resolution, adjustable focus, zoom, and contrast. Positioned at a perpendicular angle to the rice field, the camera requires a minimum distance of 1 meter from the field for optimal viewing. Additionally, solar panels are integrated into the setup to harvest energy from the sun.

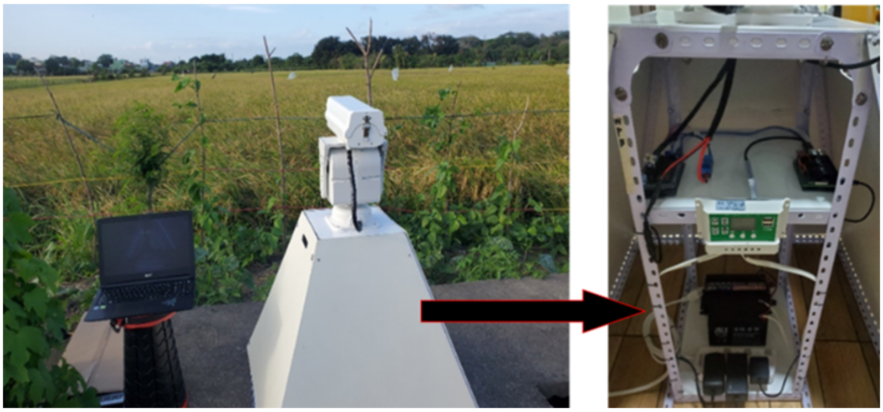

Figure 5. *System Overall Set-up*

Data gathering procedure

Fig. 6 shows the picture test setup used during data gathering, which involved various distances to assess the detection capabilities of the Philippine Sparrow and the functionality of the laser pointer. On the other hand, the field test setup was divided into four trial sections, with the detection and deterrent system tested on each side of the hectare. Each side included distance tests, similar to those conducted in the picture test, aimed at evaluating the camera's accuracy and determining whether sunlight has a significant impact on detection performance.

Figure 6. *(a) Picture test set-up, (b) Field test set-up*

RESULTS

Three tests were conducted to verify the system's accuracy. The picture test and the field test were conducted to evaluate the algorithm's accuracy at varying distances. The third test is an overall accuracy test, where trials were conducted based on distance, time, and power consumption.

Accuracy testing using images

An image of a Philippine Sparrow was used to test the accuracy of the system's detection. In Fig. 7(a), the system has detected and pointed the laser at the image of a Philippine Sparrow. An image of different types of rice field birds was used to test whether the system can detect them. Based on Fig. 7(b), it is evident that the system or the laser pointed by the system did not detect the image of different bird species.

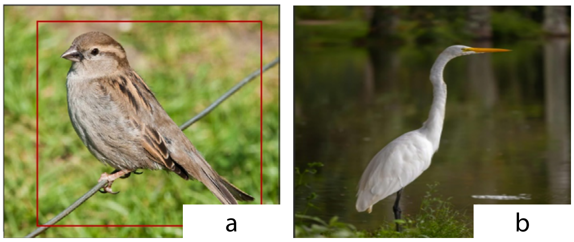

Figure 7. *(a) Detection of "Maya", (b) non-Maya birds are not detected*

Table 1 presents a summary of performance metrics recorded during the field test, including Accuracy, Error Rate, Recall, Precision, F1-Score, and Specificity, across distances ranging from 1 to 14 meters. The results reveal a clear trend: as the distance increases, accuracy and recall decrease, while the error rate increases, with the most notable drop occurring at 10 meters, where accuracy falls to 80% and recall to 60%. This suggests that distance significantly affects detection performance, likely due to reduced image resolution and environmental interference at longer ranges.

Despite consistently high precision and specificity (100 % across all distances), the decline in recall and F1-score at greater distances indicates that while the system rarely misidentifies non-pests, it may fail to detect actual pests when they are farther away—highlighting a limitation in sensitivity rather than selectivity.

To visualize this trend and provide statistical context, a line graph showing accuracy versus distance has been included, as seen in Fig. 8, with error bars representing the estimated standard deviation (±2%) based on binomial distribution assumptions. This graphical representation strengthens the interpretation of the results by illustrating performance variation across distances. Although the current study reports descriptive metrics, future work will involve repeated trials and actual standard deviation calculations to enhance statistical confidence and reliability.

Table 1. *Summary of Metric Value for Picture Test*

Metric	1 M	2 M	4 M	5 M	6 M	7 M	8 M	10 M	12 M	14 M
Accuracy	100%	100%	97%	97%	93%	90%	87%	80%	100%	97%
Error Rate	0%	0%	3%	3%	7%	10%	13%	20%	0%	3%
Recall	100%	100%	93%	93%	87%	80%	73%	60%	100%	93%
Precision	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
F1-Score	100%	100%	97%	97%	93%	89%	85%	75%	100%	97%
Specificity	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

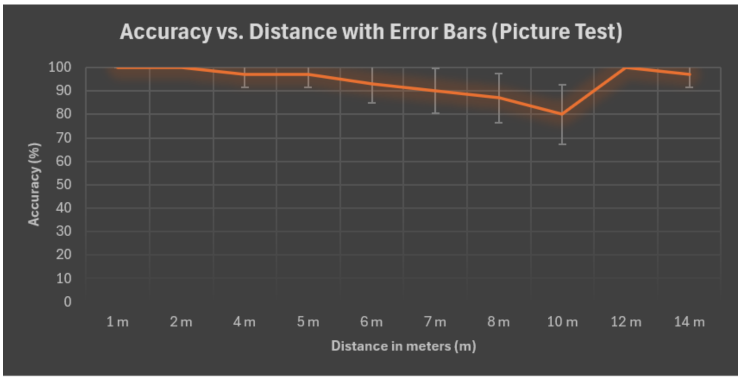

Figure 8. *This figure illustrates the system's accuracy across varying distances, with error bars representing estimated standard deviation based on binomial distribution assumptions (Picture Test Result)*

Accuracy testing in the field

The system's accuracy during field testing was evaluated based on both the distance from the target and the image quality captured by the camera. To assess performance across varying conditions, the robot was positioned at four designated locations around the farm lot, labeled Corner 1 to Corner 4. At each corner, tests were conducted at five distance intervals: 1–3 meters, 3–6 meters, 6–9 meters, 9–12 meters, and 12–15 meters. These ranges were selected to reflect typical operational distances in small to medium-sized agricultural plots, ensuring relevance to real-world deployment scenarios. For each distance range, 10 trials were performed to provide a statistically meaningful sample size while maintaining practical feasibility. Testing was conducted during daylight hours to simulate standard working conditions and ensure consistent lighting for image capture, as shown in Figs. 9 and 10.

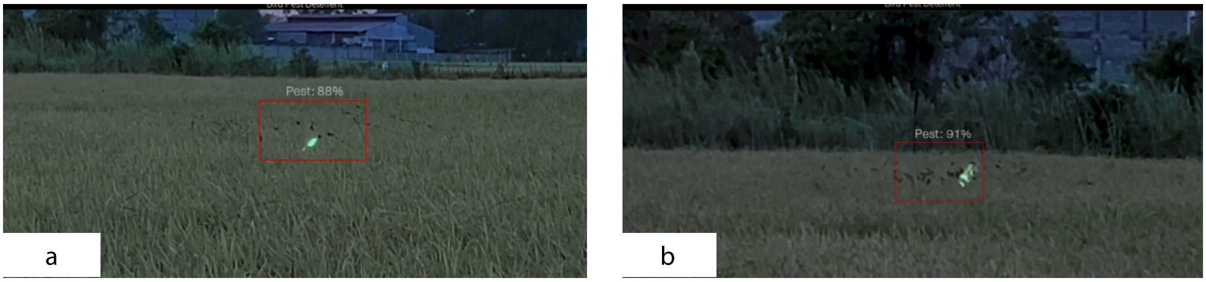

Figure 9. *(a) Morning field test, (b) Evening field test*

Table 2 shows that Corner 2 has the lowest accuracy rate and the highest error margin, which can be attributed to its orientation opposite the sun. This positioning likely causes sunlight to reflect directly into the camera, interfering with detection performance. This observation is further supported by the Accuracy vs. Corner graph with error bars as seen in Fig. 10, which visually highlights the significant drop in accuracy and increased variability at Corner 2. These results indicate that both sunlight exposure and camera positioning are critical factors affecting detection accuracy.

Table 2. *Summary of Metric Value for Field Test*

Metric	Corner 1	Corner 2	Corner 3	Corner 4
Accuracy	78%	70%	89%	84%
Error Rate	22%	30%	11%	16%
Recall	81%	71%	89%	87%
Precision	95%	89%	98%	95%
F1-Score	87%	79%	93%	91%
Specificity	40%	70%	90%	30%

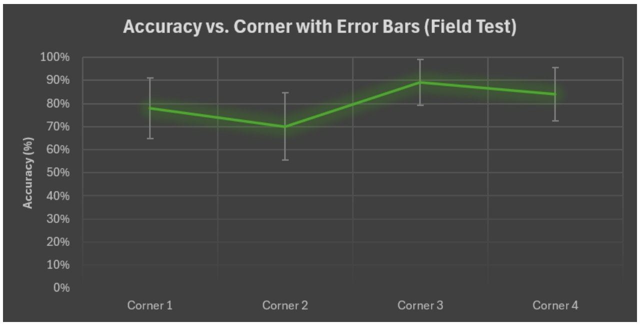

Figure 10. *This figure illustrates the system's accuracy across varying distances, with error bars representing estimated standard deviation based on binomial distribution assumptions (Field Test Result)*

Overall accuracy rate

For the overall system training, it consists of five (5) days of trial, in which we used the same ranges of distance as seen in the field test to validate if the robot is detecting and deterring the "Maya" birds. The overall testing took place from 6:30 AM to 8:30 AM (daytime) and from 4:30 PM to 6:30 PM (nighttime). Each day, we also record the actual power consumption, as shown in Fig. 11. Fig. 12 summarizes the results, where series 1 represents the evening measurement, series 3 represents the morning measurement, and series 5 represents the measured accuracy rate per distance range.

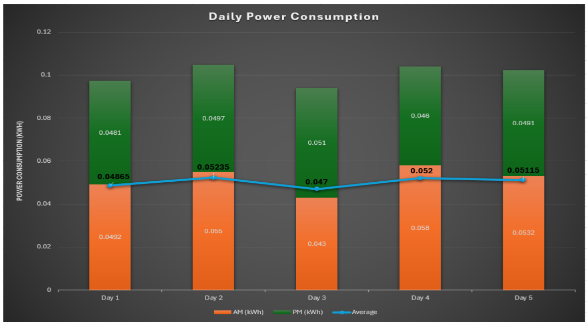

Figure 11. *Five-day results of power consumption*

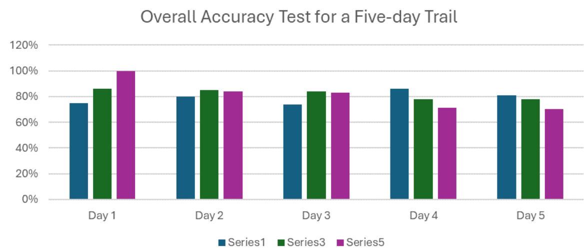

Figure 12. *Overall Accuracy Field Test*

The accuracy rate varied by distance, with the lowest accuracy, at 70%, observed between 12 and 15 meters, while the highest accuracy occurred within the 1–3-meter range. This indicates that the farther the distance, the lower the system's accuracy can reach. The primary factor contributing to this result was the distance and camera quality, as the system cannot detect bird pests at a farther distance.

Additionally, the system demonstrated a daily average power consumption of 0.050 kWh, underscoring its exceptional energy efficiency. This low power requirement translates to minimal operational costs for farmers, supporting a sustainable and economical design. Compared to traditional pest control methods, which often rely on fuel-based machinery or chemical applications, the system consumes significantly less energy, thereby reducing its overall environmental impact and making it suitable for long-term agricultural use.

Environmental conditions such as sunlight glare, dust, and fluctuating lighting can affect image quality and detection accuracy. To mitigate these challenges, the system can be equipped with optical filters to reduce glare and enhance contrast, as well as adaptive image processing algorithms that dynamically adjust to variations in lighting. These enhancements improve reliability across different times of day and weather conditions, ensuring consistent performance in real-world farm environments.

Furthermore, the system is compatible with renewable energy sources, such as solar panels, which enhances their sustainability and makes it ideal for deployment in off-grid or rural areas. In terms of scalability, the system is designed to be modular and cost-effective. A basic unit, including the camera, processing module, and solar power setup, can be assembled for approximately Php15,000 – Php 20,000, depending on component sourcing and local labor costs. This makes it accessible for smallholder farmers, mainly when supported by agricultural cooperatives or government subsidy programs. Its ease of installation and low maintenance requirements further support adoption in local contexts, offering a practical and eco-friendly approach to pest management.

DISCUSSION

This study demonstrates the feasibility of a low-power, machine-learning-based robotic system for detecting and deterring Philippine sparrows in rice fields using a green laser pointer. The system achieved high precision and specificity (100%), an overall detection accuracy of 96.4%, and a recall of 94.8% across varying distances. These metrics indicate strong reliability in minimizing crop damage and reducing the need for manual monitoring, as false negatives or missed detections pose a greater risk than false positives in pest control. In practical terms, a 96.4% accuracy can significantly reduce infestation risks and labor costs, even if it is slightly below the highest reported accuracy of fuzzy recognition-based pest detection, at 98.06% (Han et al., 2024), and deep learning models such as ASP-Det (Wang et al., 2022). However, these benchmarks often originate from controlled indoor environments, whereas our system operates in outdoor field conditions with variable lighting and complex backgrounds, making direct comparisons challenging.

Architecturally, the system utilizes a lightweight convolutional backbone designed for edge deployment on low-power microcontrollers, rather than high-end GPUs. This design prioritizes affordability and energy efficiency, trading marginal accuracy for significantly lower resource consumption. For example, while ASP-Det requires over 200 W of GPU power and costs over $1,000 in hardware, our system runs on a 5 W embedded board costing under $200-$350, enabling scalability for smallholder farms. This trade-off is critical for real-world adoption where cost and energy constraints outweigh marginal gains in accuracy. Accuracy declined at longer ranges due to optical and computational limitations: increased distance reduces pixel density and image resolution, degrading feature extraction and lowering confidence thresholds. This trend aligns with established computer vision findings that detection performance correlates strongly with image quality and scale.

Field tests revealed sensitivity to sunlight glare and camera positioning, particularly at Corner 2, where detection was least effective. Bright light introduced overexposure, while dense foliage caused partial occlusion, conditions that challenge segmentation algorithms. These limitations suggest the need for adaptive image processing techniques, such as dynamic thresholding or HDR imaging, and hardware enhancements like optical filters and improved camera modules. Incorporating real-time calibration and feedback loops could further stabilize performance under variable field conditions.

The system consumed only 0.050 kWh per day, demonstrating strong energy efficiency compared to conventional pest control methods. This low power requirement, combined with solar compatibility, makes the system suitable for rural and off-grid areas. Unlike chemical pesticides, which degrade soil health, harm beneficial organisms, and contribute to water contamination, our approach provides a non-toxic alternative that helps reduce ecological imbalance. Compared to other electronic deterrents such as ultrasonic emitters, which typically operate continuously and consume more energy, our laser-based design uses targeted activation, minimizing power draw and environmental impact. This aligns with Green AI principles and sustainable agriculture goals by reducing the carbon footprint and minimizing chemical residues. Economically, the system provides long-term benefits for smallholder farmers, offering reduced pesticide purchases, lower maintenance costs, and an extended device lifespan, which translates to significant savings over time. While chemical control may appear cheaper initially, recurring expenses for chemicals, protective gear, and soil remediation often exceed the cost of electronic solutions. By integrating renewable energy and low-power electronics, our system supports cost-effective pest management that enhances crop protection without compromising environmental integrity.

Unlike purely image-based pest detection systems that focus only on recognition accuracy, our approach integrates detection with physical intervention, offering practical advantages for real-world deployment. Green lasers were selected based on avian behavioral studies indicating that sparrows perceive green wavelengths as threatening stimuli, prompting avoidance without harm (Elbers & Gonzales, 2021; Gerken et al., 2024). To ensure responsible engineering practice, the system is designed to meet Class 3R laser safety requirements under IEC 60825 1, thereby limiting ocular hazard by restricting accessible emission and enforcing controlled beam paths to avoid direct or specular exposure (International Electrotechnical Commission, 2014). Laser intensity decreases with distance due to beam divergence, slightly reducing deterrence effectiveness at longer ranges; this is offset by adaptive targeting that prioritizes zones with higher pest activity, consistent with findings on field-based vision systems where scale and lighting variability affect performance (Mirbod et al., 2021; Wang et al., 2023).

Digital agriculture initiatives in the Philippines, such as Project SARAi (Aamoldez, 2022) and PEST D-Tech (Valdeavilla & De Guzman, 2025), have advanced IoT-driven crop monitoring and pest detection, providing farmers with timely advisories and drone-based surveillance. However, most of these solutions stop detection and data reporting, leaving pest deterrence as a manual, labor-intensive process. Our system addresses this operational gap by introducing real-time, automated deterrent capability integrated with vision-based pest detection, while maintaining ultra-low cost and low power consumption for deployment on solar-powered edge devices. This design aligns with emerging research on low-power embedded AI for agriculture (Kouzinopoulos & Manna, 2025; Wang & Gong, 2025), enabling scalable adoption in resource-constrained rural settings. At the regional level, ASEAN's Climate-Smart Agriculture framework emphasizes technologies that boost productivity while minimizing environmental impact (The Association of Southeast Asian Nations, 2023; Kozono et al., 2025). Our approach complements these goals by reducing pesticide reliance and supporting community-level deployment through networked units integrated into national digital agriculture programs. Furthermore, by mitigating pest outbreaks exacerbated by climate variability, this system contributes to broader climate adaptation strategies for sustainable farming in Southeast Asia (Putra, 2024). Finally, its energy-efficient design reflects Green AI principles, resulting in a reduced carbon footprint compared to conventional high-power models (Castellanos-Nieves & García-Forte, 2024; Ranpara, 2025).

Despite these promising results, several limitations warrant attention. The dataset used in this study exhibited limited variability in lighting, backgrounds, and pest behaviors, which raises the possibility of model overfitting and affects confidence in classification under unseen conditions. Additionally, the dataset was imbalanced, with a greater number of samples for specific bird postures than for others, which potentially biased detection performance and reduced recall for less-represented scenarios. Field tests were conducted during a single cropping season under relatively stable weather conditions, which constrain the system's demonstrated robustness. Future research should validate performance across multiple seasons and diverse ecosystems to ensure generalizability, including adaptation to other bird species beyond sparrows. Addressing these gaps will require expanding the dataset, applying data augmentation to mitigate imbalance, and leveraging transfer learning to facilitate rapid adaptation without the need for extensive retraining. Furthermore, integrating multi-sensor inputs (e.g., infrared or thermal imaging) could improve detection under low-light or occluded conditions. At the same time, adaptive algorithms and IoT connectivity can enhance real-time responsiveness and scalability for smallholder farmers.

CONCLUSION

The implementation of a system for real-time detection of the Philippine sparrow in rice fields, along with the activation of a laser pointer for deterrence, proved to be both successful and effective. The hardware setup, which included a Raspberry Pi 4 Model B, a Coral USB Accelerator, an Arduino Mega, a camera, a laser module, a pan-tilt system, and a solar-powered supply, enabled efficient detection and tracking. Initially operating at two frames per second (FPS), the system's performance was significantly enhanced by the Coral USB Accelerator, which boosted the FPS to over 20, resulting in smoother and more responsive tracking. Beyond its technical success, the system demonstrated strong potential for sustainable agricultural use. Its low power consumption, compatibility with renewable energy, and modular design make it accessible to smallholder farmers. While environmental factors such as sunlight and distance posed challenges to detection accuracy, these limitations offer clear directions for future improvements. Overall, the system presents a promising, eco-friendly alternative to traditional bird pest control methods, making a meaningful contribution to the advancement of intelligent, non-lethal pest management solutions in Philippine agriculture.

Author Contributions

M. Garcillanosa: Conceptualization, Supervision, Writing – Original Draft, Writing – Review & Editing, Project Administration, Corresponding Author; **J. C. Dela Cruz:** Supervision; **C. M. Bathan:** Software, Formal Analysis, Visualization; **C. L. de Guzman:** Investigation, Data Curation, Resources; **R. C. Vidal:** Conceptualization, Investigation, Software, Methodology, Writing – Review & Editing.

Funding

This research received no external funding.

Ethical Approval

Not applicable.

Competing interest

The authors declare no conflicts of interest.

Data Availability

Data will be available upon request.

Declaration of Artificial Intelligence Use

The authors declare that artificial intelligence (AI) tools were used solely for language editing and formatting. All scientific content, analyses, and conclusions were independently developed and verified by the authors.

REFERENCES

Aamoldez. (2022, February 21). Project SARAi: Technologies for climate smart agriculture in the Philippines. ComDev Asia (CDA). https://comdevasia.org/for-newsletter/project-sarai-technologies-for-climate-smart-agriculture-ph/

Briones, R. M. (2021). Philippine agriculture: Current state, challenges, and ways forward. Philippine Institute for Development Studies. https://doi.org/10.62986/pn2021.12

Castellanos-Nieves, D., & García-Forte, L. (2024). Strategies of automated machine learning for energy sustainability in green artificial intelligence. Applied Sciences, 14(14). https://doi.org/10.3390/app14146196

Dela Cruz, J., Ballado, A. H., Galela, S. J. B., Olegario, R. K. D., & Reyes, C. F. J. M. (2020). ET-based irrigation system with automated bird deterrent system. 2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC), 375–380. https://doi.org/10.1109/ICSGRC49013.2020.9232643

Dyck, J., & Warbick, J. (2017). Bird control in horticultural crops (OMAFRA Factsheet 17-029). Ontario Ministry of Agriculture, Food and Rural Affairs. https://files.ontario.ca/omafra-bird-control-in-horticultural-crops-17-029-en-2023-03-08.pdf

Elbers, A. R. W., & Gonzales, J. L. (2021). Efficacy of an automated laser for reducing wild bird visits to the free range area of a poultry farm. Scientific Reports, 11(1). https://doi.org/10.1038/s41598-021-92267-z

Gerken, J., Carlton, S., Shambach, A., & Garvon, J. (2024). Evaluation of laser and acoustic non-lethal bird deterrent technologies for fish farms in the North Central Region. In North Central Regional Aquaculture Center (NCRAC). Iowa State University of Science and Technology. https://www.ncrac.org/project/evaluation-laser-and-acoustic-non-lethal-bird-deterrent-technologies-fish-farms-north

Han, F., Guan, X., & Xu, M. (2024). Method of intelligent agricultural pest image recognition based on machine vision algorithm. Discover Applied Sciences, 6(10). Springer Nature. https://doi.org/10.1007/s42452-024-06224-2

International Electrotechnical Commission. (2014). IEC 60825-1:2014: Safety of laser products – Part 1: Equipment classification and requirements. https://webstore.iec.ch/en/publication/3587

Jasim, H. K., Ahmed, A., Ibrahim, A. A., & Duru, A. D. (2022). Classify bird species audio by augment convolutional neural network. 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), 1–6. https://doi.org/10.1109/hora55278.2022.9799968

Kouzinopoulos, C. S., & Manna, Y. (2025). Hardware-Aware YOLO compression for low-power edge AI on STM32U5 for weeds detection in digital agriculture. ArXiv. https://doi.org/10.48550/arxiv.2511.07990

Kozono, M., Yamada, K., & Anbumozhi, V. (Eds.). (2025). Preliminary scoping study on building and enhancing sustainable agriculture and food systems in ASEAN countries. Economic Research Institute for ASEAN and East Asia.

Lasermet. (n.d.). Safety Standards (IEC / EN / CDRH). https://www.lasermet.com/resources/safety-standards-iec-en-cdrh/

Mahmood, A. B., Gregori, S., Runciman, J., Warbick, J., Baskar, H., & Badr, M. (2022). UAV based smart bird control using convolutional neural networks. 2022 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 89–94. https://doi.org/10.1109/ccece49351.2022.9918345

Mirbod, O., Choi, D., Thomas, R., & He, L. (2021). Overcurrent-driven LEDs for consistent image colour and brightness in agricultural machine vision applications. Computers and Electronics in Agriculture, 187, 106266. https://doi.org/10.1016/j.compag.2021.106266

Notla, P., Ganta, S. R., & Jyothula, S. K. (2022). Bird detection system based on vision [Bachelor's Thesis]. Blekinge Institute of Technology

Phetyawa, S., Kamyod, C., Yooyatiwong, T., & Kim, C. G. (2022). Application and challenges of an IoT bird repeller system as a result of bird behavior. 2022 25th International Symposium on Wireless Personal Multimedia Communications (WPMC), 323–327. https://doi.org/10.1109/wpmc55625.2022.10014932

Philippine Rice Research Institute. (2021). Field guide on harmful and useful organisms in Philippine ricefields: Insects and non-insects (Revised ed.). PhilRice. https://www.philrice.gov.ph/wp-content/uploads/2023/02/Field-Guide_-Harmful-and-useful-organisms-in-Philippine-rice-fields-Insects-and-Non-insects.pdf

Philippine Statistics Authority. (2019). Agricultural indicators system: Food availability and sufficiency (2019). https://www.scribd.com/document/584227904/PSA-Agricultural-Indicators-System-Food-Availability-and-Sufficiency-2019

Putra, B. A. (2024). ASEAN's climate change mitigation and adaptation measures: abandoning stagnant policy responses. Frontiers in Climate, 6. https://doi.org/10.3389/fclim.2024.1488560

Ramadhani, M. F., & Priyambodo, S. (2024). Attacks of munia bird (Lonchura spp.) on rice crops and control carried out by farmers in Tigo Nagari, Pasaman, West Sumatra, Indonesia. World Journal of Advanced Research and Reviews, 21(1), 516–524. https://doi.org/10.30574/wjarr.2024.21.1.2654

Ranpara, R. (2025). Energy-efficient green AI architectures for circular economies through multi-layered sustainable resource optimization framework. Discover Sustainability, 6, 1031. https://doi.org/10.1007/s43621-025-01846-x

The Association of Southeast Asian Nations. (2023). ASEAN regional guidelines for promoting climate-smart agriculture (CSA) practices: Volume 3. The ASEAN Secretariat. https://asean.org/wp-content/uploads/2022/10/2023_ASEAN-Guidelines-on-the-Promotion-of-CSA-Practices-Vol-3_adopted.pdf

Valdeavilla, T. M. N., & De Guzman, M. T. L. (2025, October 7). PEST D-tech deploys drones to control pest and disease infestations in corn and onion. Department of Science and Technology, Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development. https://www.pcaarrd.dost.gov.ph/index.php/quick-information-dispatch-qid-articles/pest-d-tech-deploys-drones-to-control-pest-and-disease-infestations-in-corn-and-onion

Vantassel, S. M., Hygnstrom, S. E., Curtis, P. D., Smith, R. S., Smith, K., & Hygnstrom, J. (2015). Structural pest control bird management program: National wildlife control. National Wildlife Control Training Program. https://digitalcommons.unl.edu/icwdm_wdmconfproc/174

Wang, C., & Gong, J. (2024). Intelligent agricultural greenhouse control system based on internet of things and machine learning. ArXiv. https://arxiv.org/html/2402.09488v2

Wang, F., Liu, L., Dong, S., Wu, S., Huang, Z., Hu, H., & Du, J. (2022). ASP-Det: Toward appearance-similar light-trap agricultural pest detection and recognition. Frontiers in Plant Science, 13. https://doi.org/10.3389/fpls.2022.864045

Wang, R., Jiao, L., & Liu, K. (2023). Deep learning for agricultural visual perception: Crop pest and disease detection. Springer. https://doi.org/10.1007/978-981-99-4973-1

Zahra EL Bouni, F., El Hariri, T., Zouitni, C., Ben Bahva, I., El Aboui, H., & El Ouaazizi, A. (2021). Bird image recognition and classification using watson visual recognition services from IBMCloud and conventional neural network (CNN). 2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 1–6. https://doi.org/10.1109/icecce52056.2021.9514269

How to cite this article:

Garcillanosa, M., Dela Cruz, J., Bathan, C. M., De Guzman, C. L., & Vidal, R. C. (2025). Avian Pro: Intelligent robot for Philippine sparrow detection and deterrence using laser pointer. Recoletos Multidisciplinary Research Journal 13(2Si), 09-21. https://doi.org/10.32871/rmrj1302si.i2503