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Pest and Disease Monitoring System for Banana Lakatan Farming using CNN Algorithm

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ABSTRACT

Pest and disease control is crucial in maintaining the quality and productivity of Lakatan bananas. But conventional pest and disease monitoring approaches are inefficient and may delay the detection of pests and diseases. To overcome this problem, we built a farm control system, the Pest and Disease Monitoring System for Banana Lakatan Farming using Convolutional Neural Network (CNN) algorithm. This system employs a camera to take a photo of the banana leaves, then the CNN model classifies the image to determine the presence of pests and diseases. If a pest or disease is detected, the system automatically turns on a pump to apply the correct chemical to treat the fruit. It also includes an ultrasonic sensor to detect the level of chemicals in the tank and a voltage sensor to detect the power system and the battery. Users can also monitor and analyses the data obtained. In summary, the system offers an efficient and automated approach to pest and disease control for Lakatan banana farming, which saves farmers' time and help them increase their fruit yield with the timely detection and response.

INTRODUCTION

Banana lakatan farming is one of the main income sources of many farmers in Maasim, Sarangani Province. But farmers still struggle to cope with the challenges such as frequent cause substantial losses, and the excessive use of chemical pesticides for protection which leads to higher production cost and environmental degradation. The absence of an effective pest monitoring and control also hinder farmers' ability to keep productivity and to earn a significant profit. In response to these issues, this research provides a solution to the problem by developing a Pest and Disease Monitoring System for Banana Lakatan through the use of Convolutional Neural Network (CNN) Algorithm. The system will combine sensor devices and computer vision techniques to identify the presence of insect and potential plant disease by inspecting the images of banana trees. Using the CNN algorithm, the system identifies if the tree is infected or not, provides information on each tree to the plantation owners, and calculates the required dosage of pesticide to treat plants. The system offers automated monitoring and smart detection to facilitate sustainable Banana Lakatan farming, while enhancing farm management and decreasing wastage of pesticide.

LITERATURE REVIEW

Related Literature

Erasmo and Perito (2025) developed an Android app using CNN MobileNetV2 that detects Lakatan banana diseases with 91.07% accuracy. The app allows farmers to take leaf pictures and see results with maps and graphs, showing that mobile AI can help in fast disease detection. Gerance *et al.*, (2025) created "SaBaTech," a real-time banana pest and disease detection system using ESP32-CAM, TensorFlow, and Keras, which includes SMS alerts and reports, demonstrating that AI can support large-scale farm monitoring. Pine and Ricaña (2025) built a CNN model that classifies banana diseases with 91% accuracy using over 11,000 images. Lasco and Beltran (2024) compared different CNN models and found EfficientNet as the most accurate at 91% accuracy. Geslani *et al.*, (2024) showed that CNN performs better than DNN in banana ripeness detection with 91.24% accuracy. Ancheta *et al.*, (2025) developed a MobileNetV2-based system with 98.17% accuracy for banana leaf disease detection using mobile apps. Ibarra *et al.*, (2023) combined YOLOv4 and Raspberry Pi for the detection of Panama disease at 90% accuracy. Mendoza *et al.*, (2024), Aguilar-Hawod *et al.*, (2019), and Pauya *et al.*, (2024) also emphasized the need for banana disease monitoring, plant health and good agricultural practices in the Philippines. Yan *et al.*, (2023) developed ResNet50 to detect banana Fusarium wilt with 98% accuracy. Jiménez *et al.*, (2025) used deep learning models (EfficientNet and ResNet50) to detect 87-89% of leaf diseases in bananas in Ecuador. Keerthana *et al.*, (2024) studied banana disease prediction using soil mineral data instead of images, showing another way of disease prevention. Jeyachandra and Vasumathi (2024) developed a CNN model that classified multiple banana diseases with 92% accuracy. Kalaivani *et al.*, (2024) created an Android app that detects banana leaf spot diseases with 91.41% accuracy. Geneta *et al.*, (2024) tested several CNN models in Ethiopia, where VGG16 achieved 81.53% accuracy.

Related Studies

Several recent studies have implemented CNN-based systems for banana disease detection in real-world settings. Bhuiyan *et al.*, (2023) developed BananaSqueezeNet, a lightweight CNN model that achieved 96.25% accuracy in

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detecting Pestalotiopsis, Sigatoka, and Cordana diseases using the Bangladesh BananaLSD dataset. Elinisa and Mduma (2024) created a mobile-based CNN model for early identification of banana diseases, achieving reliable performance for smallholder farmers. Figorilli *et al.*, (2025) proposed an intelligent IoT device combined with a smartphone and 3D-printed prototype for in-field Black Sigatoka disease recognition, attaining 82% training accuracy and 78% validation accuracy. Narayanan *et al.*, (2022) developed a hybrid CNN and FSVM system that diagnosed five types of banana diseases with 99% accuracy using 3,500 field images from Southern India. Syihad *et al.*, (2023) compared ResNet50 and VGG19 for banana disease classification, with ResNet50 achieving 94% accuracy. Rajalakshmi *et al.*, (2025) designed a deep CNN that identified Sigatoka, Cordana, and Pestalotiopsis with 98.92% accuracy using 768 augmented images. Rohini and Raghavendra (2025) developed a CNN-based automated system for diagnosing four banana leaf diseases. Shafay *et al.*, (2025) reviewed deep learning methods for plant disease detection using RGB and hyperspectral imaging, highlighting the potential of AI for early detection. Locally, Gerance *et al.*, (2025) implemented SaBaTech, a web-based system using TensorFlow Keras and ESP32-CAM, which scored a mean of 3.64 under ISO/IEC 25010 evaluation. These studies confirm that CNN-based systems are effective for real-time pest and disease monitoring in banana farming.

Table 1: Hardware Components

Components	Function
Raspberry Pi 4 Model B	Main controller that processes image data and runs CNN algorithm
Arduino Uno R4	Controls sensor and execute commands for operations
WebCam (Logitech C270)	Captures images of banana plants for pest and disease detection
Ultrasonic Sensor	Measures the level of chemicals inside the container
Voltage Sensor	Monitors battery voltages and power status
12V Water Pump	Pump pesticide from the container to the nozzle
Relay 1 Channel 12V	Controls the activation and deactivation of the water pumo
Servo Motor 12V	Controls the direction of spraying mechanism
Chemical Hose	Transfers liquid from the container to the nozzle
10L Chemical Container	Stores pesticide or chemical solution
12V Worm Gear Motor	Supplies high-torque movement for driving the system
Motorcycle Chain & Wheel	Transfers motion from the motor enable system movement
5V Buck Converter	Step down voltage from 12v to 5v for Arduino and sensors
Battery	Provides powers supply to the entire system

MATERIALS AND METHODS

This system uses a dual - controller design where the main controller is Raspberry Pi 4, reprehensible for image data using CNN Algorithm, while the Arduino Uno R4

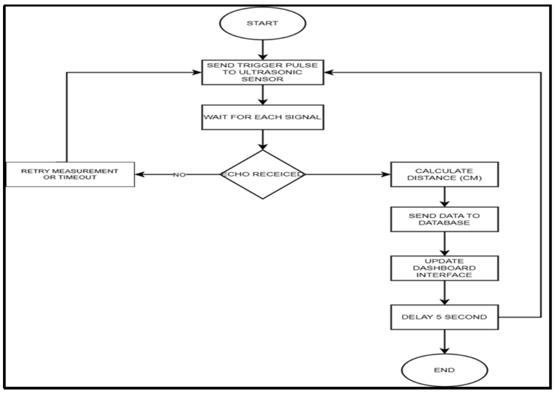

Figure 1: Hardware Flowchart

DC RS550 Motor	Execute movement of the system and support machine operation during detection and spraying
Spray Nozzle	Sprays pesticide to targeted areas

handles sensor and reading and device control.

The system operation was analyzed to determine the required hardware for banana pest and disease detection system. It continuously captures images using webcam and collects sensor data such as chemical level and battery status. This image is processed using CNN and ViT algorithm to detect pest and disease. When a problem is detected, the system automatically activates the spraying mechanism through the water pump and relay. Motors and chain drive are also used to move the position the system. All data are displayed and can be stored for monitoring.

Figure 1 shows the flowchart of hardware and software accepted data input from a webcam, an ultrasonic sensor and voltage sensor. The sensor data was fused with the image which was pre-processed and analyzed under the CNN and ViT algorithms. In event of invalidity of the information, the system reiterated the process. After the validation of the data, it was able to identify the disease and pest, the level of confidence was calculated and the necessary treatment was found. Finally, it shows the results, recommendations and battery status chemical status. This was repeated so as to continuously monitor and detect.

This system algorithm shows the pest and disease

Table 2: System Confidence Level Interpretation

Confidence Level (%)
0% - 59%
60% -74%
75% - 89%
90% - 100%

detection works automatically. First the webcam camera captures a live image of the plant. The image is sent to the system for processing. The system uses CNN and Vision Transformer (ViT) to analyze the image and check if there are any pest and disease. If nothing to found the system continues monitoring the plant. If a problem is detected, the system calculates how confident it is about the result and then show the detected issue along with the recommended treatment to the user.

This system Confidence Level Interpretation check the confidence score from the CNN and ViT models to see if the result is reliable. If the confidence is low, the system asks for new images. If the confidence meets the required level, the system confirms the result and provides the detect out along with the recommended treatment. The confidence ranges and corresponding actions are show in Table 3.

Table 3: System Confidence Level Interpretation

Confidence Score (%)	Result Reliability	System Action
0% - 59%	Low	Request new images captures
60% -74%	Moderate	Show warning and suggestion
75% - 89%	High	Display detects pest/disease with recommendation
90% - 100%	Critical	Confirm result and provide full treatment

Mathematical Expressions and Symbols

The equation for calculating the arithmetic mean to statistically analyze surveys is written as follows:

where x is the mean, ∑x is the sum of all values, and n is the number of respondents.

Respondents And Testing Procedure

The respondents were 15 farmers from Purok Kablacan Malipayon, Barangay Kabalacan, Maasim, Sarangani province who have knowledge in pest and disease management, this system testing was in five stages (1) testing all hardware components individually, including Raspberry Pi Arduino Uno R4, and sensor (2) testing the CNN model's accuracy using banana leaf and fruits images in a controlled setting (3) testing the system in real farm for real - time detection and automated spraying (4) testing system reliability during continues operation using battery (5) evaluating user experience through a five - points Likert scale survey covering usability, accuracy, functionality, interface, and hardware performance.

Statistical Treatment

Analysis of data utilized descriptive statistics in terms of the weighted mean. Five-point Likert scale was applied based on the interpretation provided below:

4.20-5.00 – Strongly Agree
3.40-4.19 – Agree
2.60-3.39 – Neutral
1.80-2.59 – Disagree
1.00-1.79 – Strongly Disagree

RESULTS AND DISCUSSION

The following discussions highlight the results obtained after evaluating the Pest and Disease Monitoring System for Banana lakatan Farming Using CNN Algorithm through 15 Lakatan farmer respondents from ALLAND LAKATAN FARMING.

The system's functionality was evaluated based on five criteria: task completion, feature usefulness, error-free operation, consistency, and meeting user needs. It obtained an overall mean of 3.74, interpreted as "Strongly Agree." The system successfully completed all tasks (3.73), provided useful features for banana Lakatan farming (4.23), and worked without errors (3.86). It also showed consistent results (3.66) and met user needs (4.73). The highest rating was for error-free operation, showing that the system was rated positively, proving that it is effective for pest and disease detection in banana farming, as suggested by Erasmo and Perito (2025).

Table 4: Functionality Evaluation Results

Functionality	Mean	Interpretation
1. The system preforms all the task needed for pest and disease monitoring.	3.73	Strongly Agree
2. The features provided by the system are useful in farming.	4.23	Strongly Agree
3. The functions of the system work properly without errors.	3.86	Strongly Agree
4. The system give consistent results when used.	3.66	Strongly Agree
5. The system's functionally meets the need of the farmers users	4.73	Agree
Total Mean	4.28	Strongly Agree

The system's accuracy was evaluated based on correct detection score, reliability, and real farm performance. It obtained an overall mean of 3.76, interpreted as "Agree." The system correctly detected pests and diseases (4.06), and the CNN and ViT models produced accurate results

Table 5: Accuracy Evaluation Results

Accuracy	Mean	Interpretation
1. The system pours out the pellets in the right manner according to the programmed schedule.	4.06	Agree
2. The sensors can give correct values based on the water quality, such as pH, turbidity, and temperature.	4.33	Strongly Agree
3. Oxygenation control is switched to the appropriate position, and it depends on the real dissolved oxygen levels.	4.73	Strongly Agree
4. The periodic information is collected in the system without delays and inconsistencies and is recorded correctly.	3.93	Agree
5. The decisions made by the computer are synchronized and perfectly agree with the current conditions of the pond: feeding, monitoring, and oxygenation.	3.86	Agree
Total Mean	4.18	Agree

(4.33). It also reduced false detection (4.73), was reliable in confidence scores (3.93) and performed well in the field (3.86). The highest rated was model performance, while reduction of false detection had the lowest rating with a very minor improvement required. The system was given a good rating for its accurate detection of pests and diseases, as recommended by Lasco and Beltran (2024).

The pest and disease monitoring system for Banana Lakatan farming using CNN and ViT algorithms is shown in Table 6. The system obtained a high overall mean of 4.77, interpreted as "Strongly Agree," indicating that it is highly effective. The highest score was 4.86, showing that the automated system performs better than manual methods. Reducing manual effort scored 4.66, while system performance scored 4.73. Overall, the results show that the system is highly effective in improving banana farming automation and management, as suggested by Pine and Ricaña (2025).

Table 6: Effectiveness Evaluation Results

Effectiveness	Mean	Interpretation
1. Accuracy pest and disease detection (accurate results and overall performance)	4.66	Strongly Agree
2. Reliability of hardware components (sensor and motors performance)	4.73	Strongly Agree
3. Automated spraying mechanism effectiveness	4.8	Strongly Agree
4. Real - time monitoring capability and consistency	4.86	Strongly Agree
5. Overall system effectiveness	4.8	Strongly Agree
Total Mean	4.77	Strongly Agree

Results for reliability dimension are provided in Table 7. The system obtained an averages score of 4.10 interpreted as “Agree,” showing good reliability. Battery ensured continuous operation 4.33, the motor also actuator worked smoothly (4.40) and sensor provided accurate reading (4.26). The CNN model and ViT (4.21) also show reliability detection with confidence levels from 75% to 96% however, lower score for error - free operations (3.86) and consistency (3.66) indicate minor variations, likely due to chance image quality. Lighting. And environmental conditions, as suggested by Elinisa *et al.*, (2025).

Table 7: Reliability Evaluation Results

Reliability	Mean	Interpretation
1.The battery provides sufficient power for continuous system operation.	4.33	Agree
2.The motor and actuator operate smoothly with minimal noise and vibration.	4.40	Strongly Agree
3.The sensors deliver consistent and accurate readings.	4.26	Agree
4.4. The CNN and ViT algorithm provides reliable detection across multiple image samples.	4.10	Agree
5.5. The system shows error-free operation and consistent performance.	3.86	Agree
Total Mean	4.10	Agree

Results for the hardware dimension are shown in Table 8. 4.5. The system received an average rating of 4.25, which is "Strongly Agree", meaning good quality. The motor and actuator achieved the highest score (4.40) and the battery achieved the second-highest score for continuous operation (4.33) and hardware for field use (4.33). The sensors also scored high (4.26) for reliable and accurate measurements, and the Raspberry Pi 4 and Arduino Uno R4 were stable in running the CNN and controlling the system. However, the lower rating for durability (3.93) indicates that some parts need to be strengthened for long-term farming operation in extreme conditions, as

Table 8: Hardware Evaluation Results

Hardware	Mean	Interpretation
1. The motor and actuator operate smoothly with minimal noise and vibration.	4.40	Agree
2. The battery provides sufficient power for continuous system operation.	4.33	Agree
3. The overall hardware setup is suitable for field deployment.	4.33	Agree
4. The sensors (ultrasonic and voltage) function consistently and accurately.	4.26	Agree
5. The hardware components are sturdy and dependable for long-term use.	3.93	Strongly Agree
Total Mean	4.25	Strongly Agree

noted by Ibarra *et al.*, (2023).

The Pest and Disease Monitoring System for Banana Lakatan Farming using CNN and ViT algorithms was assessed in five areas: functionality, accuracy, effectiveness, reliability and hardware. The system scored a grand mean of 4.32 (Agree to Strongly Agree) across the five aspects, as seen in Table 9, showing satisfactory performance. Effectiveness (4.77) was the highest, meaning the system is more effective than traditional approaches, and helps manage farms. Functionality (4.28) showed that the system performs its functions, offers helpful features, and addresses user requirements. Hardware (4.25) showed that the components are suitable for field use. Accuracy (4.18) and reliability (4.10) were also rated positively, with only minor issues in detection consistency. Overall, the results show that the system is effective, reliable, and suitable for real-world banana farming applications.

Table 9: Overall Evaluation Summary

Dimension	Weighted Mean	Interpretation
Functionality	4.28	Strongly Agree
Accuracy	4.18	Agree
Effectiveness	4.77	Strongly Agree
Reliability	4.10	Agree
Hardware	4.25	Strongly Agree
Total Weighted Mean	4.32	Strongly Agree

CONCLUSIONS

In this study, a successful design and development of a Pest and Disease Monitoring System for Banana Lakatan Farming using CNN and ViT algorithms was accomplished with the implementation of a dual-model detection approach through a combined hardware and software setup. The Raspberry Pi 4 acts as the main processor for image analysis and web server, while the Arduino Uno R4 serves as the field controller for sensor data acquisition and actuator control. The system is able to automate the process of pest and disease detection, continuously monitor chemical tank levels using an ultrasonic sensor, and track battery status using a voltage sensor. It also uses the real-time image data processed by CNN and ViT models in order to control the automated spraying mechanism through a water pump and servo motors. The web-based monitoring dashboard made it possible to remotely view detection results, chemical levels, and battery status from any location. The assessment by 15 banana farmers in Purok Malipayon, Barangay Kablacan, Maasim, Sarangani Province had a weighted mean score of 4.32 on the five-point Likert scale, which means Agree to Strongly Agree. The hardware such as the motors, sensors and battery was very stable, allowing the system to run without a problem in the field. Through the web monitoring system on Raspberry Pi, the farmers can remotely check the alerts and history of pest and diseases scanning, and monitoring the system status. The system is now running smoothly, but minor improvements are still needed in terms of detection stability and durability of some hardware components. In addition, the implemented dual-controller system is both efficient and sustainable for small-scale banana farms, making contributions towards sustainable agriculture.

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