AUTOMATED BLACK POD (PHYTOPHTHORA PALMIVORA) DISEASE DETECTION IN CACAO PODS USING UAV

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ABSTRACT

n/a **Keywords:** *n/a*

This piece of work is wholeheartedly dedicated

to my parents

Papang

and

Nanay

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Jodie

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Theobroma cacao, widely known as cacao, is one of the most economically influential crops in the world. It serves as the primary raw material for the multibillion-dollar chocolate industry, supporting the livelihoods of approximately six million small-scale farmers globally. Once harvested, cacao seeds are processed to produce cocoa powder and cocoa butter—essential ingredients used in a wide range of products, from confections and beverages to cosmetics and pharmaceuticals. Despite its global demand and economic importance, cacao cultivation faces persistent challenges from various biotic and abiotic stressors. In particular, fungal pathogens such as *Phytophthora palmivora* cause black pod disease, which has been documented to inflict significant annual yield losses Avila-Quezada et al. (2023).

Traditional disease management in cacao farms typically involves manual inspection and subjective classification of pods. The Philippine Cacao Industry Roadmap (2021) reported that this method is labor intensive and error prone, often failing to detect infections in their early stages—especially in regions with limited access to skilled agricultural labor and advanced diagnostics. In the Philippines, for example, cacao production has not kept pace with local consumption demands. Despite favorable growing conditions, the Davao Region has been recognized as the "Cacao Capital of the Philippines" Philippine Council for Agriculture and Fisheries (PCAF) (2021).

To address these threats, modern agriculture has increasingly turned to advanced technological solutions for early disease detection and intervention. Unmanned Aerial Vehicles (UAVs) and deep learning algorithms have emerged as powerful tools in precision agriculture, offering efficient and scalable monitoring of large plantations. UAVs, equipped with high-resolution cameras and multispectral sensors, can rapidly survey wide areas, while cutting-edge models like You Only Look Once (YOLO) provide high-accuracy plant disease identification **?**. Early detection during the pre-harvest phase, as supported by Upadhyay et al. (2025); Choudhary et al. (2024), enables timely interventions to mitigate crop losses and ensure quality harvests.

Existing technological interventions for cacao disease detection, such as mobile applications that utilize image processing and machine learning, have made strides in bridging the gap. For instance, Tan et al. (2018) developed AuToDiDAC, an app designed to detect black pod rot, while Tovurawa et al. used convolutional neural networks (CNNs) to classify cacao leaf diseases. However, these solutions are predominantly dependent on static image inputs and close-range data collection. As noted by Taesiri et al. (2023), such methods can cause models to focus only on the most discriminative regions of the plant, potentially missing early-stage infections or atypical symptoms that may be spread across the pod's surface. Additionally, mobile-based approaches require farmers to manually photograph individual pods, which is laborious and impractical for large-scale plantations, thereby limiting mobility and scalability.

With these challenges in mind, this study introduces a UAV-based cacao disease detection system that leverages aerial imagery and the YOLO object detection algorithm to overcome the constraints of static, close-range data collection. By capturing images from various angles and altitudes, this approach enables more comprehensive monitoring of cacao plantations. Integrating deep learning models with UAV technology allows for the detection of disease symptoms across the entire pod surface that traditional methods may miss.

The system will be developed and followed by field tests to evaluate its performance, functionality, and integration in real-world agricultural environments. Its potential for large-scale deployment in cacao farms will also be assessed, aiming to provide a scalable, efficient, and accurate disease detection solution for one of the world's most valuable crops.

1.2 Statement of the Problem

The Philippine cacao industry faces persistent challenges that hinder its ability to meet the demands of both the domestic and international market. Although the country has favorable climate conditions and fertile land, especially in the Davao Region, which represents 78% of national production, it continues to fall short of its annual production target of 50,000 metric tons. According to the Department of Agriculture (2021), this shortfall is largely due to cacao diseases, particularly black pod disease caused by *Phytophthora palmivora*, which leads to post-harvest losses of up to 90%.

Traditional detection methods rely on manual inspection, which is labor intensive, slow, and prone to human error, leading to delayed intervention and significant crop losses. Although existing studies explore machine learning and imaging technologies for cacao disease detection, they primarily use static imaging and mobile-based approaches, limiting monitoring and scalability. To address this gap, this study proposes the integration of an Unmanned Aerial Vehicle (UAV) with You Only Look Once (YOLO) technique for detection of cacao pod disease, particularly *Phytophthora palmivora*, without human effort. The system also includes geotagging, using QGIS to pinpoint where the affected cacaos are, which are processed and viewed in a web-based application where farmers can monitor their cacao farms.

1.3 Objectives of the Study

This study aims to design a UAV-based system that integrates YOLO for identifying *Phytophthora palmivora* disease in cacao pods, with GPS geotagging for precise location mapping. Specifically, it seeks to:

1. Design and configure a UAV capable of autonomous navigation over cacao farms while providing stable flight and imaging.

2. Develop and implement a monitoring system that tracks the UAV's flight status and detection for cacao pod disease.

3. Implement a YOLO-based object detection model for cacao pod detection and a classification model for identifying *Phytophthora palmivora* infection.

4. Test the system's detection accuracy, classification performance, geotagging precision, and overall operational efficiency.

1.4 Significance of the Study

This study holds significance for multiple sectors, starting with cacao farmers, who will benefit from a practical and accessible solution for early disease detection, enabling timely intervention to prevent further contamination. This proactive approach helps reduce crop losses, improve yield quality and quantity, and promote stable income and long-term sustainability in farming practices.

The cacao and chocolate industry will also gain from a more disease-resilient cacao supply, ensuring stability and reliability in the value chain, supporting both local and global markets, and maintaining consistent raw material availability to sustain production, control prices, and boost economic activity in cacao-dependent regions. For the agricultural sector, the system promotes the modernization of farming through precision agriculture technologies, enhancing productivity and sustainability, particularly in disease-prone areas.

The government can leverage the study's outcomes to align with national agricultural development goals, such as those in the Philippine Cacao Industry Roadmap, providing a basis for policy-making, funding assistance, and technology-based interventions, while contributing to Sustainable Development Goals (SDG 8 and SDG 15) by fostering sustainable agriculture, increasing farmer income, and encouraging innovation. Lastly, future researchers in precision agriculture and remote sensing can use this work as a valuable reference for further advancements in plant disease detection technologies.

1.5 Scope and Limitations

This study focuses on the development and testing of a UAV-based detection system for cacao farms in Claveria, Misamis Oriental. The system integrates three major components: (1) a YOLO-based model for detecting symptoms of *Phytophthora palmivora* infection in cacao pods, (2) GPS and QGIS for precise geolocation and mapping of affected areas, and (3) a web-based application for monitoring and visualization of results.

The scope of the system is limited to the detection of external symptoms of black pod disease, such as visible pod rot. Internal infections that are not outwardly visible cannot be identified by the current implementation. Furthermore, while the system can assist in identifying potentially infected pods, it does not automate subsequent farm management activities such as pruning or removal of diseased pods, which must still be performed manually by farmers.

The imaging capability of the UAV is also constrained by the use of a 720p camera, which may affect the level of detail captured and thus the accuracy of disease detection under certain conditions. Additional environmental factors such as lighting, weather conditions, and UAV flight stability may also influence detection performance. These limitations define the operational boundaries of the proposed system and provide considerations for future improvements.

1.6 Definition of Terms

For clarity and consistency, the following terms are defined as they are used in this study:

Dataset - A structured collection of related data, such as images of cacao pods, used to train and evaluate deep learning models for disease detection in this study.

Deep Learning Algorithms - A subset of machine learning algorithms, particularly neural networks, used to analyze large datasets and recognize patterns in images or other inputs, enhancing precision agriculture applications.

Disease Detection - The process of identifying and diagnosing plant diseases, often involving technology such as image analysis and machine learning algorithms for early intervention.

Field Tests - Practical trials conducted in real-world agricultural environments to assess the effectiveness and performance of the proposed UAV and deep learning-based system for detecting cacao pod diseases.

Geotagging - The process of adding geographical location data, such as latitude and longitude, to images or data collected by UAVs, enabling spatial tracking and mapping of disease occurrences in cacao farms.

Image Processing - The technique of manipulating and analyzing digital images using algorithms to extract meaningful information, often for detecting patterns such as plant diseases.

Phytophthora palmivora - A fungal pathogen responsible for causing black pod disease in cacao plants, which leads to significant yield losses in cacao production.

Pod - Refers to the fruit of the cacao tree that contains cacao beans; it is the primary site for disease detection, particularly for symptoms caused by pathogens like *Phytophthora palmivora*.

Pre-harvest Detection - The process of identifying signs of disease or stress in crops, specifically cacao pods, before they are harvested, allowing for timely intervention to prevent yield loss and improve crop quality.

QGIS - An open-source Geographic Information System software that provides tools for geospatial data processing, mapping, and analysis. In this study, it is used for automating geotagging and visualizing infected cacao trees.

Static Imaging - The process of capturing fixed, non-moving images, often used in traditional disease detection methods, which may miss early-stage infections or dispersed symptoms.

Unmanned Aerial Vehicles (UAVs) - Aerial devices, typically drones, that operate without a human pilot, often equipped with cameras and sensors, used for monitoring agricultural environments and gathering data for analysis.

You Only Look Once (YOLO) - An advanced real-time object detection model that can quickly identify and classify objects within images, used for detecting diseases on plant surfaces in this study.

CHAPTER 2

REVIEW OF RELATED LITERATURE

2.1 Cacao Diseases and Diagnosis

Cacao (*Theobroma cacao*) is highly vulnerable to various diseases that threaten yield and production quality. One of the most aggressive fungal pathogens is *Phytophthora megakarya*, responsible for black pod disease. This disease affects all parts of the cacao plant, including pods, leaves, and stems, particularly in humid conditions.

While *P. megakarya* is a major threat in West Africa, a different variant of this species, *Phytophthora palmivora*, is the primary cause of pod rot in the Philippines, as mentioned by Solpot (2020). This pathogen was first documented in Luzon in 1918 by Reinking and remains a significant challenge for local farmers. According to Ministry of Agriculture, Land and Fisheries, *P. palmivora* can cause annual losses of 20–30%, with severe cases reaching up to 90% under high humidity.

Studies suggest that infected cacao plants can contribute to the spread of the disease to neighboring trees. Field experiments demonstrated that pod removal reduces black pod incidence, confirming the role of contaminated pods in disease transmission. However, research by Babin (2018) later revealed that insect pests, particularly *Helopeltis bakeri*, a mirid bug, also facilitate the spread of fungal pathogens. These insects feed on pods and shoots, causing severe damage and creating potential entry points for fungal infections.

Other notable diseases affecting cacao include Cacao Swollen Shoot Virus (CSSV), Vascular-Streak Dieback (VSD), Witches' Broom Disease caused by *Moniliophthora perniciosa*, and Frosty Pod Rot (*Moniliophthora roreri*). Farmers and researchers typically distinguish between healthy and diseased cacao plants by observing specific visual symptoms on leaves, pods, stems, and roots. Initial signs include small, circular brown spots on the pod surface, as described by Ministry of Agriculture, Land and Fisheries, which expand rapidly and often emit a characteristic fishy odor if untreated.

2.2 Current Approaches to Cacao Disease Detection and Quality Control

The Philippine Cacao Industry Roadmap Department of Agriculture (2021) highlighted that most cacao farms in the country are smallholdings, managed using ancestral knowledge or experience. This includes manually identifying black pod rot and separating diseased pods post-harvest. However, this is limited in effectiveness. According to Forest Phytophthoras of the World, healthy pods exposed to pathogens can develop internal infections within 15 days, making early detection and intervention crucial.

To mitigate diseases, farmers employ cultural and chemical control methods. Sanitation and pruning, as described by Merga (2022), reduce humidity and fungal inoculum sources. Similarly, frequent harvesting minimizes pathogen load. Fungicides such as copper-based compounds and metalaxyl were also developed and remain essential when combined with crop sanitation.

In cacao classification, traditional destructive methods like the cut-test are common, though labor-intensive and less precise Nguyen et al. (2022). Advanced but complex alternatives, such as chromatographic analysis, were proposed by Quelal-Vásconez et al. (2020). Non-destructive techniques have since emerged: imaging sensors, spectroscopy, and thermal imaging Alvarado et al. (2023), with promising applications in detecting root diseases and leaf infections. For instance, Silva and Almeida (2024) demonstrated edge computing with thermal imaging for real-time leaf disease classification. Hyperspectral Imaging (HSI) and Near-Infrared (NIR) spectroscopy also help assess cacao's internal attributes like moisture, fat, and fermentation.

2.3 Pre-harvest Disease Detection

Manual inspection remains the most common pre-harvest disease detection method, though it is time-consuming and prone to errors in large-scale farms. According to Tan et al. (2018), delays in detection increase the spread of diseases like *Phytophthora palmivora*. UAVs with high-resolution cameras and multispectral sensors provide a scalable solution. Choudhary et al. (2024) demonstrated UAV-based early disease detection, capturing subtle symptoms such as pod discoloration or texture changes, often missed by manual inspection. Similarly, Upadhyay et al. (2025) highlighted UAV integration with deep learning for more robust monitoring.

UAV integration in precision agriculture improves accuracy and timeliness. UAVs cover vast areas quickly, generating large-scale datasets. Taesiri et al. (2023) emphasized that advanced image processing and geotagging enhance precision, detecting even atypical or subtle symptoms. This proactive approach ensures early intervention and reduces crop loss.

2.4 Computer-aided Cacao Disease Detection Technology in Agriculture

Alam et al. (2022) developed a drone-based monitoring system using Gaussian kernel SVM to classify vegetables into rotten and non-rotten categories, achieving 97.9% true positive rate. Similarly, Mazzia et al. (2020) refined satellite-driven NDVI indices using UAV data and CNNs for vineyard vigor maps. Vardhan and Swetha (2023) further introduced CNN-based plant disease detection using drone imagery, showing scalability even under challenging imaging conditions. These studies highlight UAVs combined with deep learning as promising tools for precision agriculture.

2.5 You Only Look Once version 8 (YOLO) for Object Detection

Deep learning, especially YOLO, has enhanced UAV-based crop monitoring. UAV-YOLO, developed by Wang et al. (2023), integrates Wise-IoU v3, BiFormer, and FFNB to optimize aerial imagery detection. Likewise, custom YOLO variants improve detection accuracy at the expense of processing speed. YOLO also excels in plant disease diagnosis: several studies have achieved over 90% accuracy on benchmark datasets, outperforming traditional ML models.

2.6 Geotagging using QGIS in Agriculture

Geotagging links crop data with precise locations, aiding decision-making in precision agriculture. Rahman (2021) used QGIS to geotag durian trees in Malaysia, integrating ground data (e.g., tree height, canopy size, soil pH) with coordinates for improved monitoring. Such methods enable more organized, spatially-aware farm management.

2.7 Synthesis

Traditional cacao disease management relied on visual inspection, pruning, sanitation, and fungicides Merga (2022). While effective to some degree, these methods depend heavily on farmer expertise and are limited by risks of misdiagnosis and environmental impact. Laboratory-based methods like PCR and chromatographic analysis Nguyen et al. (2022); Quelal-Vásconez et al. (2020) improve accuracy but are impractical for large-scale field use.

Non-destructive imaging and AI-based approaches Alvarado et al. (2023); Silva and Almeida (2024) have become viable alternatives, enabling early detection via spectral, thermal, and hyperspectral methods. Meanwhile, mobile applications such as AuToDiDAC Tan et al. (2018) and UAV-based CNNs Tovurawa et al. showcase the power of deep learning in crop disease management.

Nonetheless, reliance on static images risks missing subtle pod-level symptoms. Integrating UAVs with YOLO-based real-time detection ensures scalability, precision, and efficiency, making it a promising solution for modern cacao disease detection and smart agriculture.

CHAPTER 3

METHODOLOGY

In this chapter, we detail the methodology employed to conduct the study, providing a comprehensive overview of the research design, data collection, and analytical procedures.

3.1 Research Design

The methodology has been adopted from the Modified Waterfall Model of the Systems Development Life Cycle (SDLC). The methodology is selected due to its structured yet flexible nature, allowing for sequential phases with opportunities for feedback and refinement. This is particularly important in agricultural technology development, where both technical precision and field validation are critical. For this study, it enables the researchers to systematically design, implement, and evaluate the integration of UAV-collected imagery with YOLO for early disease detection in cacao pods, ensuring that each phase is thoroughly reviewed before progressing to the next, while still accommodating necessary adjustments. Figure 2 shows the stages necessary for development.

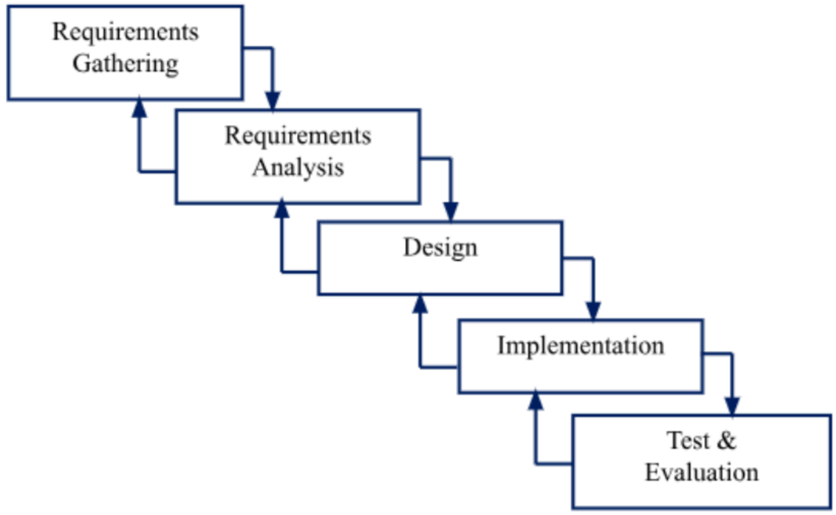

Figure 1: Modified Waterfall Model of SDLC

3.2 Data Gathering

To ensure a well-rounded and effective system design, data for this study will be collected from various relevant sources:

3.2.1 Sources of Data

Cacao Farmers and Field Personnel. Surveys and interviews will be conducted with cacao growers and farm workers to gather insights on existing practices for disease detection, common issues encountered in the field, and expectations for a UAV-based detection system. Agricultural Specialists. Input agricultural professionals will be obtained to identify key disease symptoms, validate detection criteria, and provide guidance on effective monitoring strategies for cacao pod health.

Existing Literature and Research Studies. A comprehensive review of academic and technical literature, such as studies by Baculio & Barbosa (2022), Vera et al. (2024), and Solpot (2020), will support the design of the detection system by offering benchmarks on accuracy, image processing, and the use of machine learning in agriculture.

Technology Experts. Consultations with UAV technicians, AI developers, and computer vision experts will be sought to ensure the system's technological components such as image acquisition and model training are both feasible and optimized for agricultural environments.

3.2.2 Data Gathering Procedure

To gather relevant data that will inform the design and development of the cacao pod disease detection system, this study will utilize both questionnaires and interviews.

Questionnaire. A structured questionnaire will be distributed to cacao farmers and field personnel to gather information about their current practices in detecting cacao pod diseases, the challenges they face in early identification, and their perspectives on using UAV-based solutions. Before distribution, the questionnaire will be reviewed and approved by the research adviser, agricultural specialists, and academic authorities to ensure that it is technically sound, ethically appropriate, and aligned with the objectives of the study.

Interview. Interviews will be conducted with cacao farmers, agricultural experts, plant pathologists, UAV technicians, and AI developers. These interviews aim to collect in-depth insights on disease symptoms, detection indicators, drone imaging strategies, and technical requirements for integrating YOLO into an agricultural setting.

Existing Literature. A review of relevant literature will be conducted to understand the current state of disease detection systems in agriculture, particularly focusing on cacao pod diseases. This will include studies on the use of UAVs, AI-driven disease detection models (such as YOLO), and the challenges associated with deploying such technologies in farming environments and provide a foundation for comparing the proposed system with existing solutions.

3.2.3 Data Finding Analysis

To gather relevant data, this study will employ multiple data collection methods.

Qualitative Analysis. Thematic analysis will be applied to interviews and open-ended survey responses. This approach will help identify recurring themes such as difficulties in manual disease detection, trust in machine learning techniques, and challenges related to the adoption of UAVs. Insights from this analysis will inform user-centered system design and guide improvements in usability and functionality.

Quantitative Analysis. Descriptive statistical analysis will be used for the structured survey data. This includes calculating frequencies, percentages, and average values to measure levels of technological readiness, prevalence of black pod disease, and the willingness of users to adopt UAV-based solutions for monitoring. These metrics will provide measurable indicators to support system feature prioritization.

Feasibility Analysis. Sensor specifications and machine learning model performance will be assessed through expert consultations and a review of relevant literature. This includes evaluating the accuracy of YOLO for disease detection and the practicality of drone operation in cacao farm environments using a performance matrix.

Spatial Analysis. Given that the UAV system captures geo-tagged images, spatial analysis will be conducted to examine the geographical distribution of detected disease cases. This analysis will help visualize infection hotspots across the farm and support precision intervention strategies. Tools such as heatmaps or geospatial clustering may be used to map and interpret disease spread over time and space.

3.3 Requirement Gathering

3.3.1 User Definition

Following the requirements gathering process, the primary user of the system has been identified.

Farmers - The primary user of the system, responsible for utilizing UAVs to detect early signs of cacao pod diseases and making informed decisions for crop management.

3.3.2 System Requirements

Table 1: System Requirements

Category	System Requirements
Input Requirements	The system shall collect images of cacao pods captured by UAVs for dis The system shall allow users to initiate UAV image capture and review The system shall utilize annotated image datasets for training the AI m The system shall use GPS metadata from UAVs as input to geo-tag dis The system shall accept feedback from farmers regarding detection accu

3.4 Design and Implementation

3.4.1 Context Level Diagram

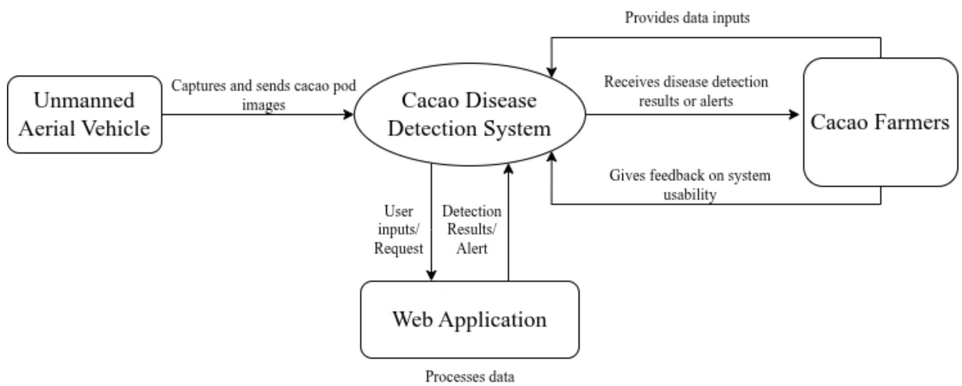

Figure 2: Context-Level Diagram of the Study

Figure 2 illustrates the context-level diagram of the cacao disease detection system. This diagram provides a high-level overview of the interactions. As a context-level diagram, it abstracts away internal processing to focus solely on how external entities interact with the system as a whole. The system integrates an Unmanned Aerial Vehicle (UAV), which is responsible for capturing and transmitting aerial imagery of cacao pods. These images serve as critical input for the system's disease detection processes. The Web Application functions as the user interface, facilitating communication between the system and its users. Through this platform, cacao farmers can input relevant field data and observations, while also receiving timely detection results. Cacao farmers contribute to the system by using the web app, submitting field data, and providing feedback for continuous improvement.

3.4.2 System Architecture

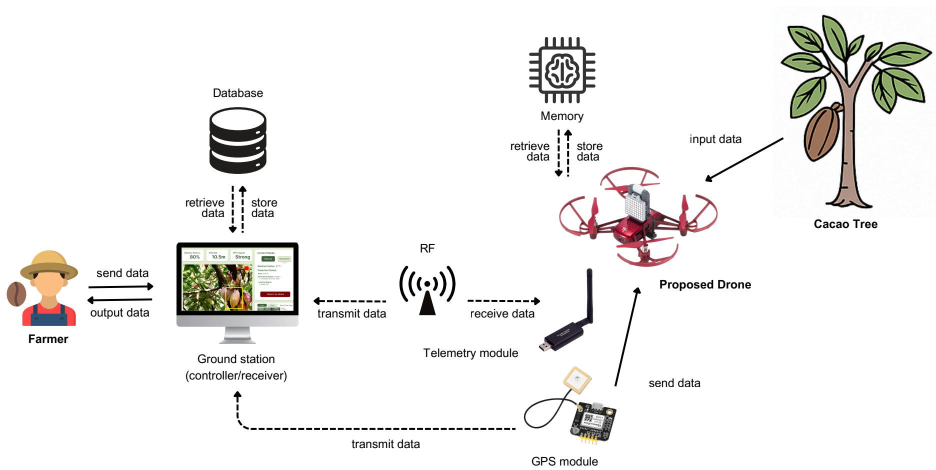

Figure 3: System Architecture Diagram of the Study

Figure 3 illustrates the system architecture of the study. The process begins with the cacao trees, which are the central focus of the system. To monitor them, a proposed drone is deployed over the farm. This DJI RoboMaster TT is equipped with cameras and sensors that collect input data—primarily images and environmental readings—from the trees as it flies at the same level as them. The data captured by the drone is transmitted to an open-source controller with a camera module, which acts as the drone's mini computer. This device processes the incoming images and sensor data. Additionally, a GPS module connected to the system sends precise geolocation data to the processor, tagging the collected images with accurate coordinates. Once the data is processed, it is temporarily stored in a memory unit. From there, the data is transmitted using a telemetry module, which serves as a bridge between the drone and the ground systems. The telemetry module sends the data wirelessly via RF to the web-based system, which acts as both a controller and a receiver. It receives the telemetry data and displays it in a user-friendly format, allowing the farmer to monitor the status of the cacao trees. The farmer can also send commands or control inputs back to the system using the system. All this information can be stored and retrieved from a database for later analysis or reference. The farmer is empowered with clear insights about the farm's condition without needing to be physically present at each tree.

3.4.3 Graphical User Interface (GUI)

Figure 4 presents the proposed Dashboard interface for cacao disease detection. The dashboard is designed to summarize critical field data in a user-friendly format, supporting timely decision-making. The top section displays pod health statistics, including the number of black pods, healthy pods, and the total detected. At the center, a satellite image visualizes drone-analyzed areas with markers indicating infected zones. A pie chart provides a comparative view of healthy versus diseased pods across zones, while a detection history log on the right records recent findings with timestamps to enhance traceability and monitoring.

3.4.4 Hardware and Software Requirements

Table 2: Hardware Requirements

Drone	DJI Robomaster TT (Tello Talent)
GPS Module	NEO-M8N

The hardware setup, summarized in Table 2, is composed of essential components that enable efficient data acquisition and geospatial referencing. The DJI RoboMaster TT (Tello Talent) drone is employed to capture aerial images of cacao pods, providing a stable and programmable platform for image collection. To ensure accurate geolocation tagging of each captured image, a NEO-M8N GPS module is integrated into the system. This GPS module delivers high-precision positional data, which enhances the reliability of spatial mapping and supports the alignment of imagery with corresponding field coordinates.

The software requirements, summarized in Table 3, specify the technologies utilized for interface development, system management, data storage, and disease detection. The front-end interface is built with Vue.js to enable user interaction and data visualization, while the back-end is powered by the Django framework, which manages system logic, workflows, and API integra-

Table 3: Software Requirements

Front-end	Vue.js
Back-end	Django
Database	PostgreSQL
API	QGIS
Web Server	Nginx
Deep Learning Framework	YOLO

tion. PostgreSQL functions as the primary database, storing user information, detection outputs, and geospatial metadata. Geospatial analysis and visualization of infected areas are facilitated through QGIS integration. The application is deployed using the Nginx web server to ensure efficient and reliable performance. For image-based disease detection, YOLO is implemented to process aerial imagery and identify signs of infection in cacao pods.

3.5 Prototype

The prototype phase will follow a structured approach focused on dataset collection, geotagging and mapping, tree clustering, sequence diagram, and system prototype.

3.5.1 Data Collection

A custom dataset will be generated using images captured by a DJI RoboMaster TT's built-in camera during scheduled flights over cacao plantations. Capturing images from multiple angles and altitudes further enhances the dataset's comprehensiveness and reliability. To ensure the model performs well in diverse real-world conditions, the dataset will include a broad range of images representing both healthy and diseased cacao pods. Data will be gathered under varying lighting conditions, weather scenarios, and backgrounds to promote generalizability and robustness in the detection process. Special attention will be given to capturing stages of infection, and degrees of pod visibility. All images will be manually annotated to label regions of interest, which is essential for supervised training of the YOLO model. The quality and accuracy of these annotations directly impact the model's ability to detect and classify diseases reliably. Image preprocessing techniques such as resizing, normalization, and data augmentation may also be applied to enhance the dataset and prevent overfitting. Once prepared, the dataset will be used to train the YOLO detection model, forming the core component of the disease recognition system.

3.5.2 Geotagging and Mapping

To support spatial accuracy and enhance the traceability of captured data, geotagging and mapping functionalities are incorporated into the system architecture. A GPS module (NEO-M8N) is integrated with DJI RoboMaster

TT open-source controller, enabling the synchronous acquisition of geographic coordinates during drone operations. As images are captured by the drone's onboard camera, corresponding latitude and longitude values are simultaneously recorded and transmitted to the database. This ensures that each image can be accurately associated with its physical location within the cacao plantation. For spatial data visualization, the system employs the QGIS API, an open-source geographic information system that facilitates the rendering of geospatial information. Through this integration, users are able to interact with an intuitive map interface displaying drone flight paths, image capture points, and disease detection zones.

3.5.3 Command-based Mission Control with Robomaster TT SDK

Software Development Kit will be utilized in this study to implement command-based mission planning with the DJI RoboMaster TT. Through the SDK, the drone can execute scripted flight commands such as takeoff, forward(x), back(x), cw(angle), and land, enabling it to follow predefined flight paths across cacao rows. During these missions, the drone will capture images of cacao pods at specific intervals, which are then paired with location data provided by the integrated NEO-M8N GPS module. Unlike real-time processing systems, this study adopts an offline detection approach, where the collected images and GPS coordinates are stored and later processed using the YOLO algorithm. The results of the detection are then mapped in QGIS to identify and visualize areas affected by Phytophthora palmivora. This method allows the researchers to demonstrate a functional mission planning workflow that synchronizes drone navigation, image acquisition, and geotagging, while accounting for the RoboMaster TT's hardware limitations.

3.5.4 Flowchart of Hardware and Software

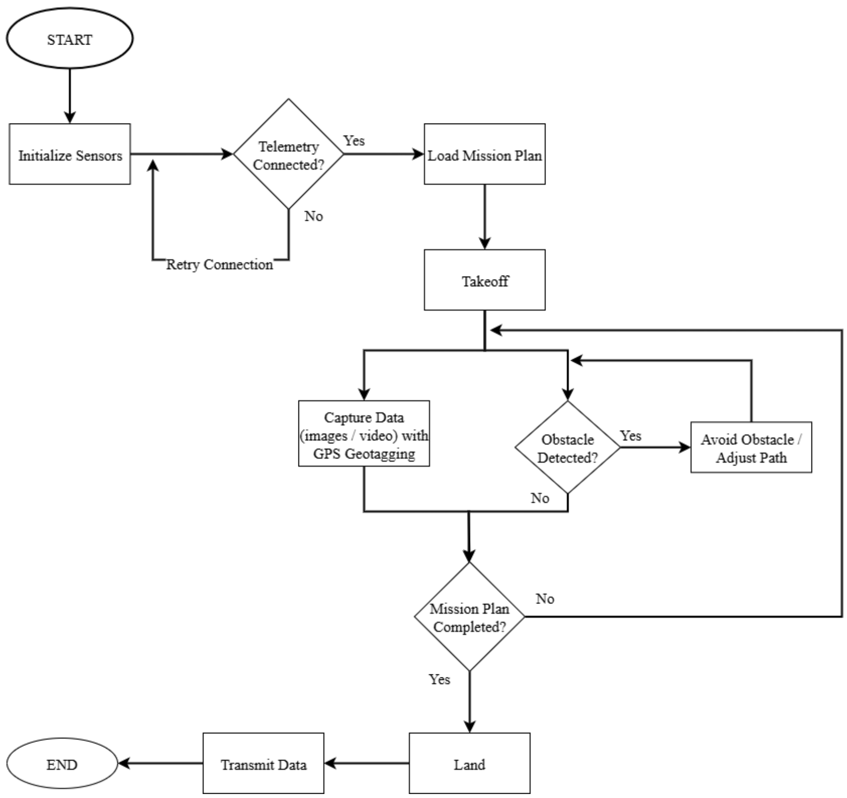

Figure 4: Hardware Flowchart

Figure 5 illustrates the operational workflow of the UAV system; it begins with powering on the UAV, followed by the initialization of its key sensors, including the camera, GPS module, and obstacle detection system. Once the sensors are active, the system checks for telemetry connectivity with the ground station; if the connection fails, the drone retries until successful. After establishing a link, the mission plan is loaded from the ground station, and the UAV proceeds to takeoff. During flight, two processes run in parallel:

the drone continuously captures images and videos with GPS geotags for later processing, while simultaneously monitoring its environment for obstacles and adjusting its path when necessary. The system then checks whether the mission plan has been completed. If it is complete, the UAV proceeds to land; if not, it continues executing the remaining tasks until completion. Only after landing are the stored image and location data transmitted to the ground station for processing. The operation then concludes with system power down.

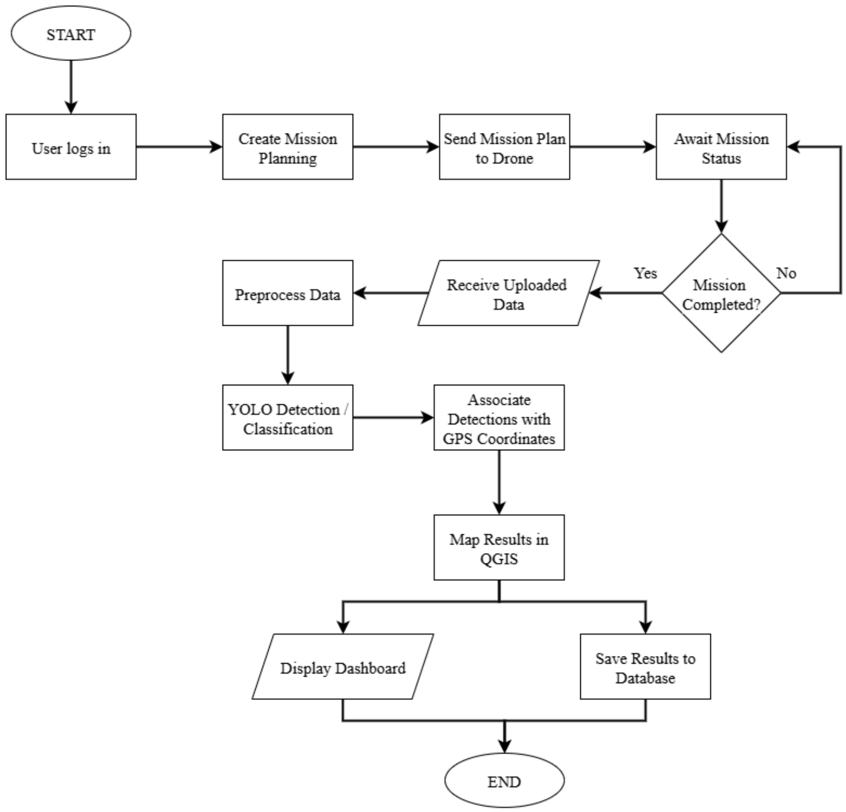

Figure 5: Software Flowchart

Figure 6 shows the software workflow, starting with the user logging into the system and creating a mission plan that defines waypoints, altitude, and capture intervals. This plan is then sent to the UAV through SDK, after which the system awaits mission status updates. At this stage, a decision point determines whether the mission has been completed. If the mission is successful, the system retrieves the uploaded images with their GPS metadata; otherwise, it continues waiting until completion. Once the data is received, the images undergo preprocessing such as resizing, normalization, and augmentation before being passed through the YOLO algorithm for disease detection and classification. The detection results are then associated with GPS coordinates to ensure spatial accuracy and are mapped in QGIS to generate a clear visualization of affected areas. From this stage, two operations run in parallel: results are displayed on the dashboard for immediate user insight, while the same results are saved into the database for reporting and long-term storage. Finally, the processes converge, and the mission concludes to complete the workflow.

3.6 Testing

Testing was conducted to ensure that the system operates accurately, efficiently, and is suitable for real-world use in cacao farm management. The process involved functional testing, usability testing, and performance testing. Functional testing verified whether key features—such as UAV image capture, detection of Phytophthora palmivora-infected cacao pods using the YOLO, and geotagging of infected trees—performed as intended, with each function tested through defined inputs and expected outputs. Usability testing assessed how easily end users, particularly cacao farmers, could navigate and interact with the system by performing essential tasks such as logging in, accessing detection results, and interpreting geotagged maps. Feedback was collected using the System Usability Scale (SUS) to evaluate the overall user experience. Performance testing measured the system's responsiveness and accuracy, focusing on the time taken from image capture to the display of results, as well as the efficiency in processing high-resolution images and managing data. Together, these tests validated the system's reliability, user-friendliness, and effectiveness in supporting early disease detection and timely intervention.

3.6.1 Functional Testing

Functional testing will be carried out to ensure that every part of the system works as intended. This testing will begin once the prototype is complete. It will focus on verifying key features, such as capturing images through the drone, detecting healthy and infected cacao pods using the YOLO, tagging infected trees' locations with GPS, and displaying results clearly on the dashboard. Each function will be tested by giving specific inputs and checking if the outputs match what is expected. For example, the drone should respond correctly to manual and automatic commands, and the system should accurately identify pods and show their locations on the map. This testing helps find and fix any errors or missing functions, making sure the system is reliable and ready for real-world use.

3.6.2 Usability Testing

Usability testing will be conducted to make sure the system is easy and practical for cacao farmers to use. After the prototype is ready, farmers will be invited to try important features such as logging in, flying the drone, viewing pod detection results, and checking the map showing infected trees. After using the system, they will fill out a short survey called the System Usability Scale (SUS), which measures how user-friendly the system feels. The survey uses a rating scale from 1 to 5 and asks about how easy the system is to learn, how confident they feel using it, and whether the features work well together. Scores are converted to a total out of 100, with scores above 68 generally meaning the system is easy to use. This process will help the team understand what works well and what needs improvement before the system is fully deployed.

3.6.3 Performance Testing

Performance testing is conducted to evaluate the system's responsiveness, accuracy, and overall reliability based on its core functionalities. This includes measuring the accuracy of detecting Phytophthora palmivora-infected cacao pods using the YOLO, assessing the precision of geolocation through GPS module and QGIS, and recording the system's response time from image capture to the display of results on the dashboard. The test is carried out under standard operating conditions to determine whether the system can process high-resolution images efficiently and deliver real-time outputs. The results of this evaluation are essential in verifying that the system meets its intended performance criteria and is capable of supporting timely and informed decision-making in cacao disease management.

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the findings from the research conducted and provides a thorough analysis and interpretation of these results.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This chapter provides the summary of the results obtained in this study and gives some recommendations for further investigation.

5.1 Summary of Findings

The study's findings address the initial research questions by confirming the effectiveness, reliability, and diverse applications of telemetry systems. The "Summary of Findings" section provides a concise overview of the key results from your research. This section should be factual and focus on presenting the data without interpretation. It should include:

Key Results:

Briefly summarize the most significant findings. Use bullet points or numbered lists for clarity if appropriate. Present the data as it was found, highlighting major patterns, relationships, or trends. Data Presentation:

Include tables, graphs, or charts that succinctly summarize the data. Make sure each visual aid is clearly labeled and includes a brief description. Coverage of Research Questions:

Address each of the research questions or hypotheses posed at the beginning of the study. Summarize the results relevant to each question.

5.2 Conclusion

The "Conclusions" section interprets the findings and discusses their implications. This section should:

Interpret Findings:

Provide an interpretation of the data summarized in the previous section. Discuss what the results mean in the context of the research questions or hypotheses. Implications:

Explain the significance of the findings. Discuss how the results contribute to the field of study or practical applications. Limitations:

Acknowledge any limitations in the study that may affect the results or their interpretation.

5.3 Recommendations

The "Recommendations" section provides actionable suggestions based on the study's findings and conclusions. This section should:

Practical Applications:

Offer specific recommendations for practitioners, policymakers, or other stakeholders based on the findings. Future Research:

Suggest areas for further investigation that could address the study's limitations or build on its findings. Implementation:

Provide guidance on how the recommendations can be implemented effectively.

APPENDICES

Type your appendix here.

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I hereby declare that this submission is my own work and, to the best of my knowledge, it contains no materials previously published or written by another person, nor material which, to a substantial extent, has been accepted for the award of any other degree or diploma at USTP or any other educational institution, except where due acknowledgement is made in the manuscript. Any contribution made to the research by others, with whom I have worked at USTP or elsewhere, is explicitly acknowledged in the manuscript.

I also declare that the intellectual content of this manuscript is the product of my own work, except to the extent that assistance from others in the project design and conception or in style, presentation and linguistic expression is acknowledged.

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