LUPAD: Localized UAV-based Black Pod Rot (*Phytophthora Palmivora*) Automated Disease Detection in Cacao Pods

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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 (Wickramasuriya and Dunwell, 2018). Once harvested, cacao seeds are processed to produce cocoa powder and cocoa butter—essential ingredients in a wide range of products, from confections and beverages to cosmetics and pharmaceuticals.

The global chocolate market is projected to grow significantly from 129.1 billion dollars in 2025, and up to 178.7 billion dollars by 2035 (Future Market Insights, 2025). However, Exquisito Chocolates (2025) reported that West Africa, which supplies over 70% of the world's cocoa, have experienced a 13.1% year-on-year decrease in cocoa output in 2024 (from 5.044 to 4.382 million tons), which constitutes a drastic decline in yield. This is largely driven by black pod disease caused by Phytophthora species, with Phytophthora megakarya recognized as the dominant and most destructive pathogen in the region (Opoku et al., 2007a; Guest and Keane, 2024).

A comparable situation is observed in the Philippines. While P. megakarya dominates West Africa, black pod disease in the Philippines is primarily caused by Phytophthora palmivora (*P. palmivora*). The Davao Region, the country's major cacao-producing area and officially recognized as the "Chocolate Capital of the Philippines" (Philippine Council for Agriculture and Fisheries (PCAF), 2021), has experienced production declines associated with this pathogen. Although cacao is affected by multiple diseases, black pod rot, locally referred to as *butikol*, caused by *P. palmivora* has been documented to induce substantial annual yield losses, posing a persistent threat to the sustainability of the Philippine cacao industry (Avila-Quezada et al., 2023). These losses were further corroborated through a field interview with the owner of the Janog Cacao Plantation.

The Janog Cacao Plantation is a 5-hectare cacao farm with over 2,500 cacao trees planted located in Initaon, Misamis Oriental. The owner report yield fluctuations between 100–500 kg of cacao beans, with 300 kg considered satisfactory and anything below 200 kg representing a deficit. If some infected pods are left unnoticed, they can become active infection reservoirs that accelerate outbreak progression. On average, the Janog farm recorded only about 9 in 10 cacao trees are unhealthy, as the disease can quickly spread to nearby pods if infected ones are not pruned or removed promptly. However, completing a full manual inspection cycle requires walking the entire plantation and can take up to three weeks. This on-foot, tree-by-tree monitoring reflects the current dependence on visual scouting, an approach widely described as labor-intensive and error-prone, especially for catching infections at their earliest stages (Department of Agriculture, 2021).

To address these persistent 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 cacao plantations. UAVs, equipped with high-resolution cameras and multispectral sensors, can rapidly survey wide areas, while cutting-edge models such as You Only Look Once (YOLO) provide high-accuracy plant disease identification (Vyas and Dutt, 2023). 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. (2025) 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 cacao plantations, thereby limiting mobility and scalability.

With these challenges in mind, this study introduces a UAV-based cacao disease detection system that integrates the You Only Look Once (YOLO) object detection algorithm to address the limitations of static, close-range data collection. This approach enables a convenient monitoring of cacao plantations, such as the Janog Cacao Plantation, where manual inspection is physically demanding and time-consuming. Integrating deep learning model with UAV allows for the detection of disease symptoms across the entire pod surface that traditional methods may miss. In addition to detecting infected cacao pods, the study requires a geospatial mapping component to translate detections into location-specific farm actions. QGIS is used to convert UAV

GPS-tagged detections into spatial layers and maps that identify affected areas and trees, enabling targeted intervention and repeat monitoring rather than relying on general farm-wide estimates; these geotagged results are then visualized in a web-based platform so farmers can efficiently monitor plantation health and prioritize treatment.

The proposed system will be developed followed by field tests at Janog Cacao Plantation in Initao, Misamis Oriental, to evaluate its performance and functionality in real-world agricultural environment.

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 P.*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.

1.3 Objectives of the Study

This study aims to design and develop a UAV-based system that detects P.*Palmivora* disease in cacao pods using deep learning model (object detection and disease detection) and GPS geotagging for precise location mapping. Specifically, it seeks to:

1. Configure a UAV capable of autonomous navigation over cacao farms.

2. Integrate an object detection model for cacao pod detection and a classification model for identifying black pod rot disease, or *P. palmivora* infection.

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

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

1.4 Significance of the Study

The study will be conducted at Janog Cacao Plantation in Initao, Misamis Oriental. This will hold significance for multiple sectors within the agricultural and technological landscape. By field-testing a UAV-based disease detection system in an actual cacao farm setting, the research may demonstrate the feasibility and practical benefits of integrating precision agriculture technologies into local farming operations.

For cacao farmers, particularly those managing plantations like Janog Cacao Plantation, the system may offer a convenient solution for early disease detection. It may enable timely intervention to prevent further contamination, helping reduce crop losses, improve yield quality and quantity.

For the cacao and chocolate industry, the study may contribute to sustaining both local and global markets by maintaining consistent raw material availability, controlling production costs, and supporting economic growth in cacao-dependent regions.

For the agricultural sector, the research may promote the modernization of farming through precision agriculture and remote sensing technologies. It may enhance productivity and sustainability, particularly in disease-prone areas where manual inspection is labor-intensive and inefficient.

For the government and policymakers, the study's outcomes may serve as a basis for aligning technological innovation with the goals of the Philippine Cacao Industry Roadmap. It may provide valuable insights for policy formulation, funding assistance, and small to medium-scale implementation of technology-based interventions. Further, it may contributes to the realization of Sustainable Development Goals (SDG 8: Decent Work and Economic Growth, and SDG 15: Life on Land) by promoting sustainable agriculture, increasing farmer income, and fostering innovation.

Lastly, for future researchers, this study will serve as a reference for further exploration and enhancement of precision agriculture systems, UAV applications, and plant disease detection technologies. It will also provides a real-world benchmark for testing similar systems under tropical agricultural conditions.

1.5 Scope and Limitations

This study will focus on the development and testing of a UAV-based disease detection system for cacao farms in Initao, Misamis Oriental. The system integrates three major components: (1) a YOLO-based model for detecting cacao pods; (2) a YOLO-based model to detect visible symptoms of Black Pod Rot infection in cacao pods; (3) GPS and QGIS for efficient geolocation and mapping of affected trees; and (4) a web-based application for monitoring and visualization of detection results.

The study is limited to identifying external symptoms of black pod disease such as visible pod rot and discoloration. Internal infections that do not manifest outwardly cannot be detected by the current implementation. Moreover, while the system can assist in identifying potentially infected pods, it does not automate subsequent farm management tasks such as pruning or removal of diseased pods, which must still be performed manually by farmers. QGIS is included to transform GPS-tagged detections into hotspot maps and tree-level location references for monitoring; however, spatial accuracy remains dependent on UAV GPS precision and capture distance.

The imaging capability of the UAV is constrained by the use of a 720p camera, which may limit the level of visual detail captured and affect detection accuracy under certain environmental conditions. External factors such as lighting, weather conditions, and UAV flight stability may also influence detection performance.

Despite these constraints, the programmable nature of the UAV allows the use of its Software Development Kit (SDK) to define autonomous flight paths, enabling systematic data collection across cacao rows. However, the degree of automation depends on the reliability of the programmed commands and the environmental conditions encountered during flight missions.

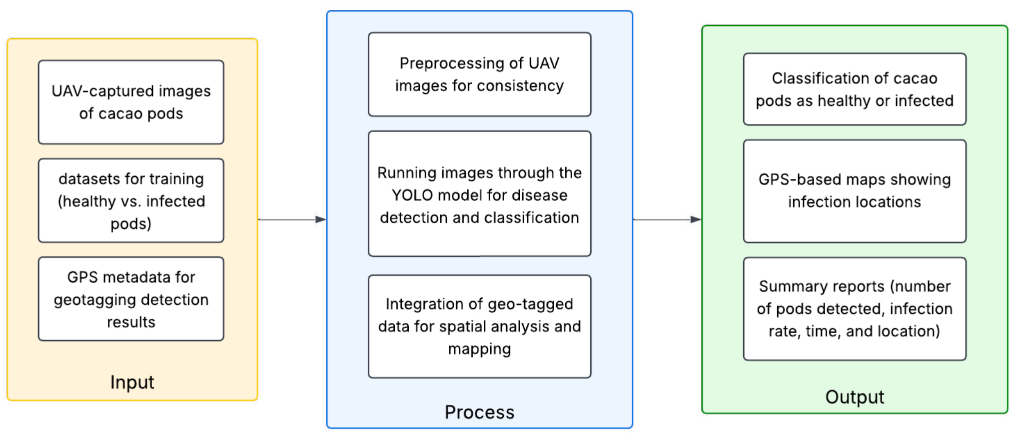
These limitations define the operational boundaries of the proposed system and provide considerations for future improvements.

1.6 Conceptual Framework

The study's conceptual framework is presented through an Input-Output-Process Model in Figure 1.1.

Figure 1.1

IPO Model



The process begins with the input stage, where drones are used to capture images of cacao pods in the farm. These images serve as the primary source of information and are compared with sets of sample images showing both healthy and diseased pods. Along with the images, location data is recorded so that each detection can be linked to its exact place in the farm.

The information collected then moves to the process stage. Here, the pod images are first checked to make them clear and consistent for analysis. After this, the system studies the images to identify whether pods are healthy or show signs of disease. The location data gathered during drone flights is combined with the results, allowing the system to create maps that show the areas where diseases may be present. This stage transforms raw images into useful information that can guide farmers in managing their crops.

In the output stage, the system produces results that are directly useful for farm management. These include the classification of cacao pods as healthy or infected, maps that point out exactly where the infected pods are located, and summary reports. The reports provide details such as the total number of pods detected, the percentage that are infected, and the specific times and places where infections were found.

1.7 Definition of Terms

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

Bounding Box - A rectangular box generated by the YOLO model to localize and highlight detected objects, such as healthy or diseased cacao pods, within an image.

Convolutional Neural Network - A deep learning architecture for visual analysis, serving as the backbone of the YOLO model 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.

Ground Station - The control and monitoring interface (web application) where UAV mission results, disease detections, and geotagged mappings are displayed for farmers.

Ground Sampling Distance - The distance between pixel centers measured on the ground, used to estimate real-world size from UAV-captured images.

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

Object Detection - A computer vision technique used to identify and locate multiple objects within an image, as performed by the YOLO model in this study.

***Phytophthora palmivora* (P.*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 P.*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.

Telemetry - The process of wirelessly transmitting data, such as flight status and image acquisition logs, from the UAV to the ground station.

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

This chapter presents relevant information and related studies that support the development of the proposed system.

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, as discussed by Andrews et al. (1997). This disease affects all parts of the cacao plant, including pods, leaves, and stems, particularly in humid conditions.

In West Africa, *P. megakarya* is a major threat, whereas in the Philippines, a different variant, *Phytophthora palmivora* (P.*Palmivora*), is the primary cause of pod rot, 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 Acebo-Guerrero et al. (2012), *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 conducted by Ndoumbe-Nkeng et al. (2004) demonstrated that pod removal reduced black pod incidence by 22% and 31% in the first year and by 9% and 11% in the second year, 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, as supported by Guest (2007).

Farmers and researchers distinguish between healthy cacao plants and those infected with diseases by observing specific visual symptoms on various parts of the plant, such as leaves, pods, stems, and roots. Initial signs include small, circular brown spots on the pod surface, as described by the Ministry of Agriculture, Land and Fisheries). These spots rapidly expand, turning dark brown or black, eventually covering the entire pod. Under wet conditions, white fungal growth may appear on the lesions. Infected pods often emit a characteristic fishy odor and, if untreated, become blackened and mummified.

2.2 Current Approaches to Cacao Disease Detection and Quality Control

Traditional Methods

The Department of Agriculture (2021) highlighted that most cacao farms in the country are owned and managed by smallholding farmers, many of whom have acquired farming knowledge through ancestral practices or personal experience. This includes manually distinguishing between cacao pods with black pod rot, then separating them after harvest. However, this approach has limitations. According to Forest Phytophthoras of the World, once exposed to pathogens, healthy pods may develop internal infections within 15 days, making early detection and intervention crucial. Delays in identifying and removing infected pods reduce the effectiveness of disease management efforts and increase the likelihood of disease spread, especially in pre-harvest settings.

To mitigate cacao diseases, farmers employ several cultural and chemical control methods including sanitation and pruning, according to Acebo-Guerrero et al. (2012). Pruning improves air circulation and reduces humidity, creating less favorable conditions for fungal growth. On the other hand, sanitation involves removing diseased pods and plant debris, helping eliminate sources of inoculum (increase immunity to a disease) and prevents reinfection.

Additionally, Merga (2022) highlighted that farmers frequently harvest cacao pods to reduce the inoculum load of pathogens such as *Phytophthora spp.*, thereby minimizing disease transmission. Scientists and fungicide experts developed copper-based compounds and metalaxyl to control black pod disease, as reported by Opoku et al. (2007b). When combined with crop sanitation, fungicide application has been shown to significantly reduce disease incidence and improve yields.

Destructive and Non-destructive Disease Detection

In cacao classification, traditional destructive techniques are often employed to assess the quality of cocoa beans. Among these methods, Nguyen et al. (2022) reported that the cut-test stands out as the most widely used due to its simplicity and effectiveness—it involves slicing beans to inspect mold, germination, and fermentation. Though practical, it is labor-intensive and less precise. With this, Quelal-Vásconez et al. (2020) introduced chromatographic analysis, which offers a higher level of sensitivity, capable of detecting metabolites and contaminants even in trace quantities. While highly reliable, chromatographic analysis is more complex and requires specialized equipment, making it less accessible for routine quality control in cacao production. Since these approaches are destructive in nature, they result in the loss of sampled beans, making it less ideal for large-scale quality control.

In contrast, Alvarado et al. (2023) listed non-destructive techniques such as imaging sensors, spectroscopy, and thermal imaging to monitor plant health. These methods facilitate the early detection of diseases, allowing for timely interventions that can prevent the spread of infections and reduce crop damage.

For instance, a study on ginseng root diseases highlighted the urgency of developing efficient non-destructive testing methods for early-stage detection and limiting further spread. Silva and Almeida (2024) explored edge computing for real-time classification of leaf diseases using thermal imaging, which converts infrared (IR) radiation into visible images. Near-Infrared (NIR) Spectroscopy and Hyperspectral Imaging (HSI) also analyze internal attributes of cacao, such as moisture content, fermentation levels, and fat composition (Alvarado et al., 2023). Additionally, imaging-based computer vision detects surface defects and size variations, enhancing quality control, reducing waste, and ensuring better cacao processing outcomes.

Pre-harvest Disease Detection

Pre-harvest disease detection is significant in maintaining crop health and preventing losses. Traditional methods, such as manual inspection, have been shown to be labor-intensive, time-consuming, and prone to human error, especially in large-scale cacao farming. According to Tan et al. (2018), these limitations often result in delayed detection and intervention, which can lead to the spread of diseases like P.*Palmivora*, a major cause of black pod disease in cacao. Researchers have emphasized the importance of early detection tools to address these challenges, highlighting that timely interventions can significantly reduce crop damage and yield loss. According to Choudhary et al. (2024), UAVs equipped with high-resolution cameras and multispectral sensors offer an efficient solution, enabling farmers to monitor large areas in real-time and detect disease symptoms before they become widespread. This technology allows for early identification of subtle symptoms, such as discoloration or texture changes in leaves and pods, which are often missed by manual inspections, as pointed out by Upadhyay et al. (2025).

The integration of UAVs in precision agriculture has been increasingly recognized for its ability to enhance the accuracy and speed of disease detection. According to Vyas and Dutt (2023), UAVs can cover vast agricultural areas quickly, providing farmers with comprehensive, up-to-date data. This system not only improves the timeliness of disease detection but also enables targeted actions to mitigate disease outbreaks. According to Taesiri et al. (2023), by combining UAV technology with advanced image processing and geotagging, the detection process becomes more precise, ensuring that even subtle and atypical symptoms are identified. This proactive approach to disease management during the pre-harvest phase is essential for reducing crop losses and improving the overall sustainability and productivity of cacao farming.

Computer-aided Cacao Disease Detection Technology in Agriculture

Recent advancements in cacao plant disease detection have leveraged artificial intelligence (AI) and image processing to improve classification accuracy and disease management. These methods, as stated by Upadhyay et al. (2025), automatically learn and extract intricate features from raw image data, capturing subtle patterns associated with specific diseases. They surpass traditional manual methods, leading to improved detection accuracy.

One such study by Baculio and Barbosa (2022) introduced an objective classification system for cacao pods. Their model combines Local Binary Pattern (LBP) features and a Color Histogram (CH) with an Artificial Neural Network (ANN) to differentiate between healthy and unhealthy pods. This research underscores the importance of machine learning in agricultural diagnostics, ensuring that disease identification is both efficient and accurate. Similarly, Tan et al. (2018) developed AuToDiDAC, an automated mobile tool designed to detect black pod rot, one of the most devastating diseases affecting cacao plants.

Another notable contribution comes from Basri et al. (2020), who proposed a mobile image processing application for identifying pests and diseases in cacao fruit. Their deep learning-powered system processes real-time images, categorizing fruits as healthy, pest-infected, or disease-affected with high accuracy. A subsequent review by Basri et al. (2020) further explored the role of image processing in modern cocoa plantations, revealing that color-based disease detection models achieve an average accuracy of 82.85%. The authors advocate for integrating machine learning models to optimize disease prediction and support precision agriculture.

Meanwhile, Buenãno Vera et al. (2024) proposed a deep learning model for diagnosing monilia and black pod diseases in cacao pods. Using EfficientDet-Lite4, their model was trained on a dataset of diseased and healthy pods and later deployed in a mobile application to assist farmers. The app's intuitive design and real-time disease identification make it a valuable tool, particularly for small-scale farmers with limited access to expert guidance.

Building on these innovations, Tovurawa et al. (2025) applied deep learning and Exploratory Data Analysis (EDA) to cacao disease detection. Their research focused on a custom Convolutional Neural Network (CNN) that outperformed other models in accurately classifying cacao diseases. By utilizing a dataset from Ghanaian cacao farms, this study provides a locally relevant solution that could enhance crop resilience and farmer livelihoods.

2.3 Unmanned Aerial View (UAV) Technology in Agriculture

The advancement of drone-based technologies and deep learning algorithms has significantly contributed to precision agriculture, particularly in large-scale crop monitoring and quality assessment. Alam et al. (2022) developed a drone-based crop product quality monitoring system that utilizes vision cameras and a Gaussian kernel support vector machine (SVM) to classify vegetables into rotten and non-rotten categories. Their approach extracts chromatic, contour, and texture features from image datasets of tomatoes, cauliflower, and eggplants to enhance classification accuracy. The system demonstrated a 97.9% true positive rate and 95.4% overall accuracy, highlighting its effectiveness in agricultural product quality monitoring.

Similarly, Mazzia et al. (2020) explored the refinement of satellite-driven vegetation indices using UAVs and machine learning. While satellite imagery plays a crucial role in crop monitoring, its limitations in capturing detailed intra-row crop variations can lead to inaccuracies. Their study proposed a deep learning framework that integrates high-resolution UAV multispectral data to improve Normalized Difference Vegetation Index (NDVI) maps. By training a convolutional neural network (CNN) with UAV-acquired datasets, their approach produced refined NDVI maps that provided more accurate crop status assessments. This refinement enabled the generation of 3-class vineyard vigor maps using a K-means classifier, offering a valuable tool for site-specific crop management.

In a related study, Vardhan and Swetha (2023) introduced a deep learning-based approach for detecting plant diseases using drone-captured imagery. Their model utilized a convolutional neural network (CNN) trained on a comprehensive dataset of plant species exhibiting various diseases. The study demonstrated high proficiency in disease classification and detection, even under challenging imaging conditions. By integrating real-time drone monitoring with deep learning, their approach presents a scalable and efficient solution for improving plant health assessment, further advancing the role of smart agriculture in modern farming practices.

2.4 You Only Look Once versions (YOLO) for Object Detection

The You Only Look Once (YOLO) framework has become one of the most influential deep learning models for real-time object detection. Its successive versions have continuously evolved to address limitations in accuracy, speed, and computational efficiency. According to Ultralytics Terven et al. (2023), the YOLO family progressed from YOLOv1 to the most recent YOLO11, each version integrating new architectural strategies and optimization methods to improve detection across diverse applications.

YOLOv8, released in January 2023, introduced an anchor-free decoupled head design, separating classification from bounding box regression. This design enhanced optimization, particularly for small-object detection, and allowed flexible deployment through multiple model sizes (Nano to X), enabling a tradeoff between speed and accuracy Wang et al. (2023). YOLOv8 also extended its capabilities beyond detection to include classification and segmentation, making it versatile in agricultural monitoring and disease diagnosis tasks Vyas and Dutt (2023).

YOLOv9, launched in February 2024, improved feature aggregation by incorporating *Programmable Gradient Information (PGI)* and the *Generalized Efficient Layer Aggregation Network (GELAN)*. These innovations enhanced the retention of gradient information across layers, thereby boosting detection accuracy while maintaining efficiency for edge devices and mobile platforms, according to Vina (2025). Furthermore, YOLOv10, released in May 2024, further optimized object detection by introducing a *Non-Maximum Suppression (NMS)-free* design through consistent dual-label assignment. This improvement allowed more stable predictions across multiple objects, eliminating redundant bounding boxes and enhancing both training efficiency and precision in dense detection environments, as reported by Vina (2025).

The latest version, YOLOv11, released in September 2024, emphasized efficiency and scalability. With approximately 22% fewer parameters than YOLOv8m while achieving higher mean Average Precision (mAP), YOLOv11 demonstrated superior accuracy-to-complexity performance. Benchmark evaluations confirmed its ability to outperform YOLOv8, YOLOv9, and YOLOv10 in both detection accuracy and inference speed, making it well-suited for large-scale and resource-constrained agricultural applications, as described by Vina (2025).

Table 2.1

Comparison of YOLO Versions

YOLO Version and Key Features	**Release Year**
YOLOv8 — Introduced an anchor-free and decoupled head architecture; enhanced small-object detection and supported multi-task learning (detection, classification, segmentation).	2023
YOLOv9 — Integrated Programmable Gradient Information (PGI) and GELAN for improved gradient preservation, feature aggregation, and detection accuracy on edge devices.	2024 (February)

YOLO Version and Key Features	Release Year
YOLOv10 — Adopted a Non-Maximum Suppression (NMS)-free framework with consistent dual-label assignment; improved stability and precision in dense detection scenarios.	2024 (May)
YOLOv11 — Achieved 22% parameter reduction compared to YOLOv8m while attaining higher mean Average Precision (mAP); optimized for scalability, efficiency, and inference speed.	2024 (September)

Across the YOLO series, continuous improvements will be made in terms of accuracy and efficiency. Earlier versions such as YOLOv3 and YOLOv4 will establish the foundation for reliable object detection, while YOLOv8 will introduce a more efficient, anchor-free design. According to Vina (2025), YOLOv11 offers a strong balance of speed and accuracy for detecting small and complex objects. In Ultralytics' COCO benchmarks, YOLOv11 detection models achieve mAP50–95 from 39.5 (YOLO11n) up to 54.7 (YOLO11x) at 640 px, demonstrating the accuracy speed trade off across variants. For this study, YOLOv11 is selected to support real-time UAV operation under varying field conditions, and its detection performance will be quantified using standard validation metrics including Box Precision (P), Recall (R), mAP@0.5, and mAP@0.5:0.95 on the cacao dataset.

Overall, the progression from YOLOv8 to YOLOv11 demonstrates continuous refinement toward models that maintain competitive accuracy while improving efficiency for deployment. According to Vina (2025), YOLOv11 improves the accuracy–efficiency trade-off by reducing parameter count while achieving strong detection performance, which is relevant for real-time UAV-based monitoring under varying illumination, motion effects, and canopy occlusion. Therefore, YOLOv11 is selected as the primary model for this study because its efficiency-oriented design supports real-time UAV operation while maintaining detection accuracy for small and visually complex cacao pod lesion patterns.

2.5 Geotagging using QGIS in Agriculture

Geotagging plays a vital role in precision agriculture by connecting crop-related data with specific locations in the field. This spatial connection helps farmers make smarter, more targeted decisions about managing their crops. For example, Mohidem et al. (2021) showed that combining geotagged aerial images with vegetation indices significantly improves how accurately crop conditions can be monitored. This makes it easier to spot and address issues in particular areas of the field. Likewise, Rahman (2021) used QGIS software to geotag individual durian trees in Malaysia's Kluang Valley. By linking each tree's location with detailed ground data—such as tree height, canopy size, soil pH, and leaf dimensions—the study created a more precise and efficient way to monitor the health and growth of each tree. This method allowed for a more organized and data-driven approach to plantation monitoring by enabling the spatial joining of field measurements with geographic coordinates. Rahman (2021) highlights the effectiveness of QGIS in supporting precise andefficient geotagging workflows, underscoring its relevance as a valuable tool in agricultural decision-making and crop health assessment.

2.6 Synthesis

Cacao pod health is typically distinguished through visual parameters such as the presence of brown or black lesions, surface discoloration, and texture changes, often accompanied by a characteristic odor in advanced stages. These visual cues, as identified by the Department of Agriculture (2021)and Philippine Council for Agriculture and Fisheries (PCAF) (2021), serve as the primary parameters to differentiate healthy from diseased pods.

Traditionally, manual inspection and post-harvest destructive testing—including cut-tests and chromatographic analysis—have been used to identify diseases like Phytophthora palmivora-induced black pod rot (Acebo-Guerrero et al., 2012; Opoku et al., 2007b). While effective for confirming disease presence, these methods are labor-intensive, time-consuming, and dependent on farmer expertise, leading to inconsistent results and delayed intervention. Destructive tests, in particular, result in the loss of sample pods and are not ideal for large-scale or continuous quality monitoring (Nguyen et al., 2022; Quelal-Vásconez et al., 2020).

These limitations have prompted the adoption of computer-aided disease detection methods, such as image processing and deep learning models, which provide non-destructive pre-harvest assessment (Alvarado et al., 2023; Silva and Almeida, 2024). Pre-harvest detection offers a significant advantage—it is non-destructive, allows early diagnosis, and reduces the spread of infection, unlike traditional post-harvest evaluation.

However, existing computer-aided systems often rely on static, close-range images or mobile-based platforms, limiting spatial coverage and operational efficiency in large plantations (Baculio and Barbosa, 2022; Tan et al., 2018). These constraints can result in inconvenient detection of disease symptoms across the entire cacao pod.

To address these gaps, this study introduces a UAV-based cacao disease detection system that uses YOLO object detection for identifying both cacao pods and disease symptoms. Based on comparative analysis, YOLOv11 demonstrates the most effective balance between speed, precision, and scalability, particularly in detecting small and complex objects ((Vina, 2025)).

Moreover, it integrates UAV aerial imaging for large-scale and real-time monitoring and GPS geotagging using QGIS for precise localization of affected areas. This integration overcomes the coverage and data-collection limitations of prior systems, enabling efficient detection of P. palmivora infection in cacao farms.

CHAPTER 3

METHODOLOGY

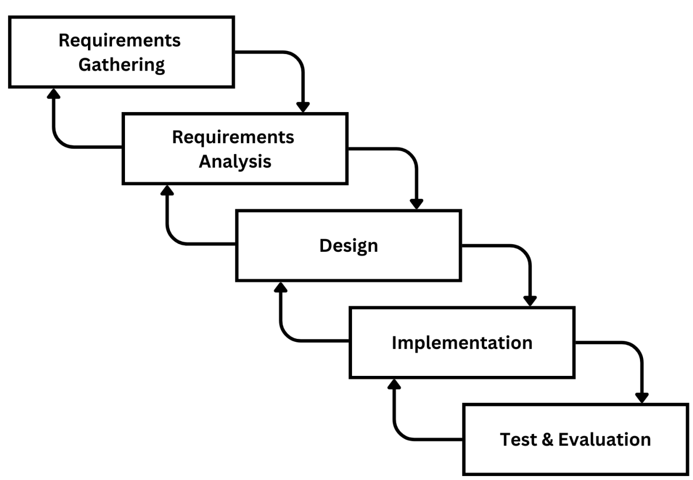
This chapter will present the methodology of the study. It will describe the research design, setting, data-gathering procedures, and the planned design and implementation of the proposed system to ensure that the study will be conducted systematically and aligned with its objectives.

3.1 Research Design

This study will adopt the Modified Waterfall Model of the Systems Development Life Cycle (SDLC), shown in figure 3.1, as its methodology.

Figure 3.1

Modified Waterfall Model of SDLC



The methodology will be selected due to its structured yet flexible nature, allowing for sequential phases with opportunities for feedback and refinement. This will be particularly important in agricultural technology development, where both technical precision and field validation will be critical. For this study, it will enable 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 will be thoroughly reviewed before progressing to the next, while still accommodating necessary adjustments.

3.2 Research Setting

The proposed study will be conducted at the Janog Cacao Plantation located in Initao, Misamis Oriental, as shown in Figure 3.2.

Figure 3.2

Janog Cacao Plantation in Initao, Misamis Oriental

The plantation covers an area of approximately five (5) hectares and contains around 2,500 cacao trees. Each tree has an average height of 2 to 2.5 meters and is planted at 3-meter intervals, forming organized rows that are suitable for structured UAV flights. The site represents a typical small to medium-scale cacao farm in the region and is relevant to the Philippine cacao industry, which continues to face challenges from black pod disease.

Local farmers will serve as potential end-users, providing feedback on the practicality of UAV operations and the usability of the detection system. The plantation's accessibility to the research team, along with its realistic farming conditions where advanced monitoring systems are rarely implemented, makes it an ideal setting for developing and testing the proposed system.

3.3 Research Setup

The research setup will utilize a UAV (Unmanned Aerial Vehicle) equipped with a built-in high-definition camera and GPS module to conduct low-altitude monitoring of the cacao farm. The UAV will operate at approximately 1 meter above ground level to capture detailed visual information of cacao pods under the canopy, where early symptoms of black pod rot are more visible than in high-altitude passes. The UAV will follow predefined flight paths along the corridors between cacao rows to ensure systematic coverage of the plantation, utilizing the existing farm layout to define the traversal trajectory.

Figure 3.3

UAV Flight Paths Across the Cacao Farm

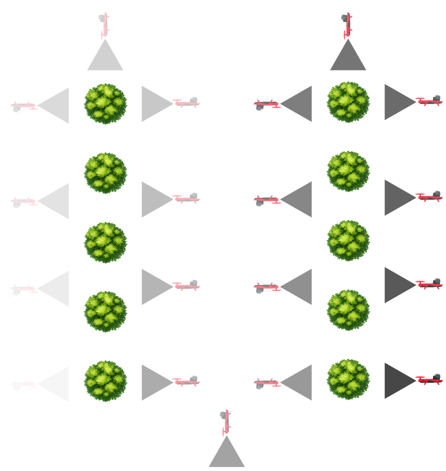


Figure 3.3 presents the UAV's flight paths across the cacao farm, illustrating the specific orientation strategies used to minimize blind spots. While the UAV moves parallel to each cacao row, it maintains a yaw (heading) orientation such that the camera faces the cacao trees during recording. This side-facing strategy keeps pods consistently inside the camera field of view and reduces missed captures caused by limited viewpoints. To address pod occlusion caused by leaves and branches, the UAV implements multi-view coverage by alternating its facing direction across passes (e.g., right-facing on one pass and left-facing on the return pass). Smooth turns at row ends (U-turns) are

performed to transition to the next row segment, ensuring stable real-time YOLO inference for detecting visible symptoms of *Phytophthora palmivora*.

3.4 Data Gathering

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

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, issues encountered in the field, and expectations for a UAV-based system.

Agricultural Specialists. Input from agricultural professionals will be obtained to identify key disease symptoms, validate detection criteria, and provide guidance on monitoring strategies for cacao pod health.

Existing Literature and Research Studies. A review of literature, including studies by Baculio & Barbosa (2022), Vera et al. (2024), and Solpot (2020), will support system design by providing benchmarks on accuracy, image processing, and 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.

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.

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.

3.5 Requirement Gathering

This section presents the requirements gathering conducted by the researchers. The data were collected through an interview with a local cacao farmer who has extensive experience in cacao production and management. The purpose of this interview was to understand the existing farming practices, challenges in disease detection and management, and collect essential information for system development.

Before the engagement, the researchers prepared a set of open- and closed-ended questions to guide the discussion. A consent letter outlining the ethical use of the collected information was also presented to the respondent, ensuring that all gathered data would be used solely for academic and research purposes in compliance with data privacy regulations. (Refer to Appendix A)

The respondent has been cultivating cacao for nine (9) years and manages a farm covering approximately five (5) hectares with more than 2,500 cacao trees planted at a spacing of three (3) meters per tree. The farm contains various elements, including tall coconut trees that provide shade, nearby power lines, and a river, none of which significantly affect the farm's operations. The farmer personally inspects the cacao pods on foot, as this is currently the only available method to monitor the trees for pest infestations and diseases.

According to the respondent, major challenges in cacao farming include high costs and labor-intensive practices, particularly in spraying, pruning, and pest control. However, the most critical issue arises during the rainy season, as it contributes to the spread of Phytophthora, the fungus responsible for black pod rot, locally referred to as butikol. During these periods, only about one (1) out of every ten (10) trees remains healthy, and the number of harvestable pods varies significantly depending on weather conditions.

The farmer identifies diseased cacao pods primarily through their appearance, observing signs such as discoloration and the presence of small dark dots, which are associated with Phytophthora infection. Once symptoms appear, even at an early stage, the affected pods are immediately removed to prevent further contamination of nearby fruits. Although spraying is conducted as a preventive measure, some infected pods remain unnoticed due to the vast area of the farm and the intensity of labor required.

Farm inspection is done daily, taking approximately three (3) weeks to complete a full cycle across all areas of the farm. The farmer increases inspection frequency during the rainy season, as losses are significantly higher compared to the dry season. Fertilizers are also applied for quality control, with an estimated expenditure of thirty thousand pesos (₱30,000) per cycle.

During the peak harvest season, typically from November to December, the farm produces around 300 to 500 kilograms of cacao beans, which are sold to vendors from Davao at a price of ₱300 per kilogram. However, yields lower than 200 kilograms are considered a deficit. Based on the respondent's estimate, approximately twenty (20) pods are required to produce one (1) kilogram of beans. The pods vary in color red to orange, and green to yellow with yellow pods indicating ripeness. Harvesting and pruning are performed manually using pruners or saws, with extra care taken to avoid damaging the fruit-bearing branches. (see Appendix B)

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.

Table 3.1

System Requirements

Category	**System Requirements**
Input Requirements	- The system shall collect images of cacao pods captured by UAVs for disease detection. - The system shall allow users to initiate UAV image capture and review sessions through a simple interface. - The system shall utilize annotated image datasets for training the AI model, specifically focusing on black pod disease. - The system shall use GPS metadata from UAVs as input to geo-tag disease detection results.
Process Requirements	- The system shall process captured images using the YOLO model to identify and classify diseased cacao pods. - The system shall preprocess input images for consistency.

Category	System Requirements
	- The system shall utilize a labeled image dataset of cacao pods. - The system shall include a manual annotation process where images are labeled with infection presence and location.
Output Requirements	- The system shall display detection results, highlighting infected areas on cacao pods in real-time or after processing. - The system shall classify each detected pod as either healthy or infected. - The system shall provide GPS coordinates alongside detection results for mapping infected areas. - The system shall generate summary reports including: total number of pods detected, number and percentage of infected pods, detection time and location.
Control Requirements	- The system shall implement secure access with user authentication to ensure that only authorized users (farmers) can access the system. - The system shall maintain logs of image captures, analysis sessions, and user feedback for audit and traceability. - The system shall validate all image inputs and user entries to ensure efficient and usable data is processed.
Performance Requirements	- The system shall be capable of processing high resolution images in real-time or near real-time with minimal latency. - The system shall efficiently manage and store large datasets of images and detection results, supporting scalable usage over time. - The system shall maintain uptime and availability to ensure uninterrupted use during farming operations.

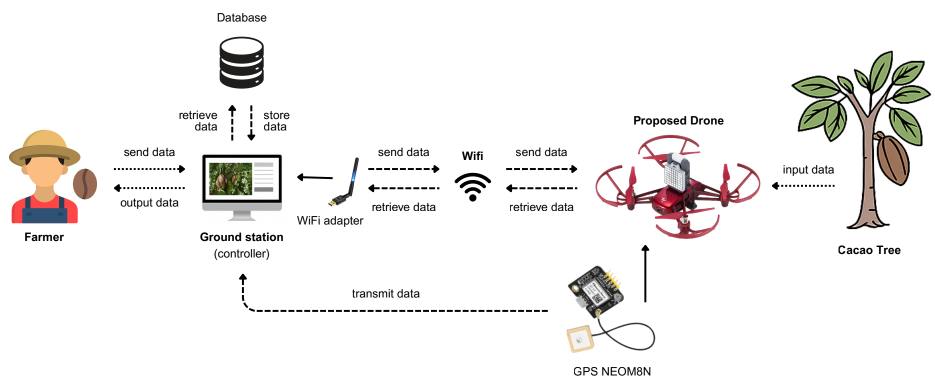
3.6 Design and Implementation

3.6.1 System Architecture

Figure 3.4 illustrates the system architecture of the study.

Figure 3.4

System Architecture of the Study



The architecture is designed as a closed-loop system centered around the cacao tree, which serves as the source of input data. The proposed drone (DJI RoboMaster TT) acts as the primary data acquisition unit, capturing visual input from the trees. To ensure spatial accuracy, an external GPS NEO-M8N module is integrated into the drone's expansion board; this module continuously transmits geolocation data to the drone, allowing for the synchronization of images with specific coordinates.

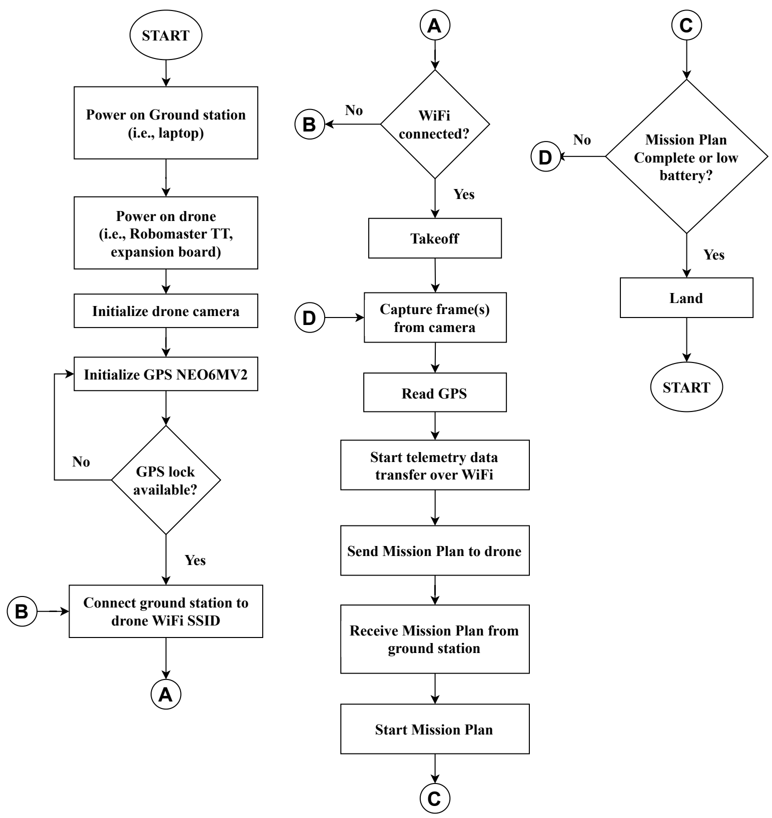
Data transmission is facilitated through a wireless Wi-Fi network. A high-gain Wi-Fi adapter connected to the ground station establishes a bidirectional link, enabling the system to send flight commands to the drone and retrieve telemetry and video data in real-time. The ground station functions as the central controller and processing hub, where the farmer interacts with the system. The farmer inputs mission parameters ("send data") and receives actionable insights ("output data") regarding the health status of the crops. Finally, a database is integrated with the ground station to permanently store mission logs and detection results, allowing for the retrieval of historical data for long-term analysis.

3.6.2 Flowchart of Hardware and Software

Figure 3.5 illustrates the operational workflow of the UAV system.

Figure 3.5

Hardware Flowchart

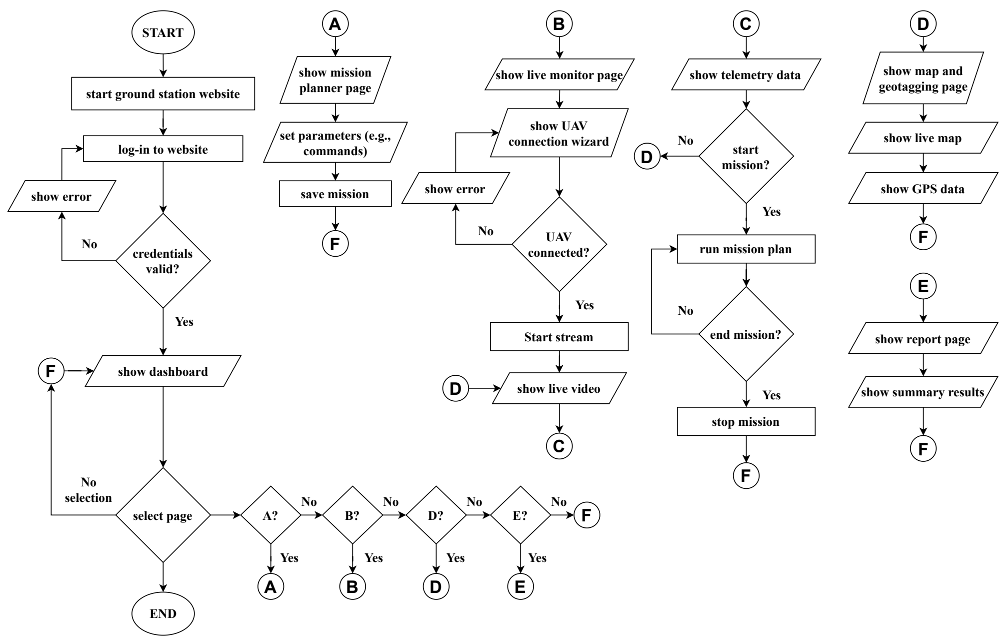


The process starts with powering on the ground station (laptop) and the UAV (RoboMaster TT and expansion board). Following startup, the system initializes the drone camera and the GPS NEO-M8N module. A critical check is performed to ensure a stable GPS lock is available; if the lock is not acquired, the system retries until it is confirmed. Once the GPS is locked, the ground station connects to the drone's Wi-Fi SSID, and the system verifies the connection status. Upon successful connection, the drone takes off and enters the main mission loop. In this loop, the drone captures frames from the camera, reads the GPS coordinates, and immediately starts telemetry data transfer over Wi-Fi. The system then manages the mission plan execution and continuously checks if the mission is complete or if the battery is low. If either condition is met, the drone lands to conclude the operation.

Figure 3.6 illustrates the user interaction flow within the web-based ground station.

Figure 3.6

User Flowchart

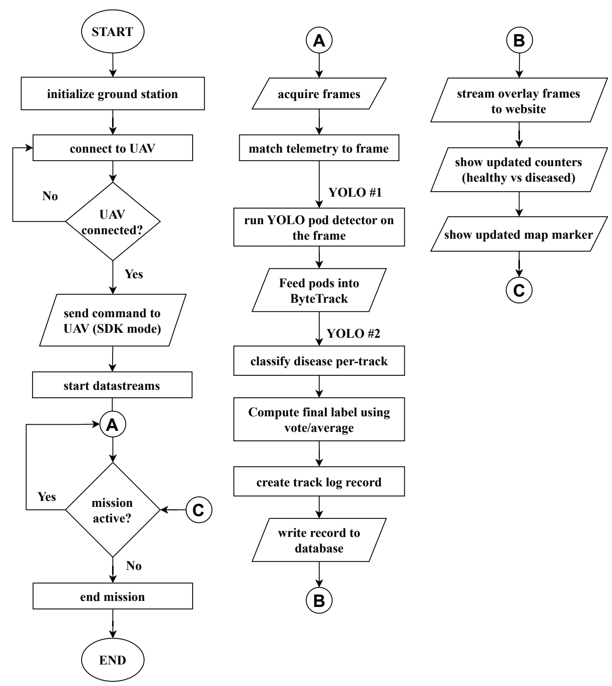


The process begins when the user opens the ground station website and logs in. The system validates the entered credentials; if invalid, an error message is shown and the user is redirected back to the login step. Once authenticated, the user is taken to the dashboard, where they can navigate to different modules by selecting a page. From the dashboard, the user may open the Mission Planner page (A) to configure mission parameters (e.g., commands) and save the mission, then return to the dashboard. The user may also open the Live Monitor page (B), where a UAV connection wizard is displayed; if the UAV is not connected, an error is shown and the connection attempt repeats, but if connected, the user starts the video stream and views the live video feed. From there, the user can proceed to the Telemetry page (C) to view telemetry data and decide whether to start the mission. If the mission is started, the system runs the mission plan until the user ends the mission, after which the mission is stopped and the flow returns to the dashboard. Alternatively, the user may open the Map and Geotagging page (D) to view the live map and GPS data, or open the Report page (E) to view the summarized results. After completing any module, the flow returns to the dashboard, allowing the user to continue navigating or end the session.

Figure 3.7 illustrates the software workflow, which begins with the initialization of the ground station and the establishment of a connection with the UAV.

Figure 3.7

Software Flowchart



Once the drone is successfully connected, the system sends SDK commands to specific flight modes and initiates the data streams. The core processing loop involves acquiring video frames and synchronizing them with telemetry data. A multi-stage detection pipeline is then executed: first, a primary YOLO model detects the cacao pods within the frame. These detections are fed into the ByteTrack algorithm to maintain consistent object identities across frames. Subsequently, a secondary YOLO model classifies the disease status of each tracked pod, and a final label is computed using a voting or averaging mechanism.

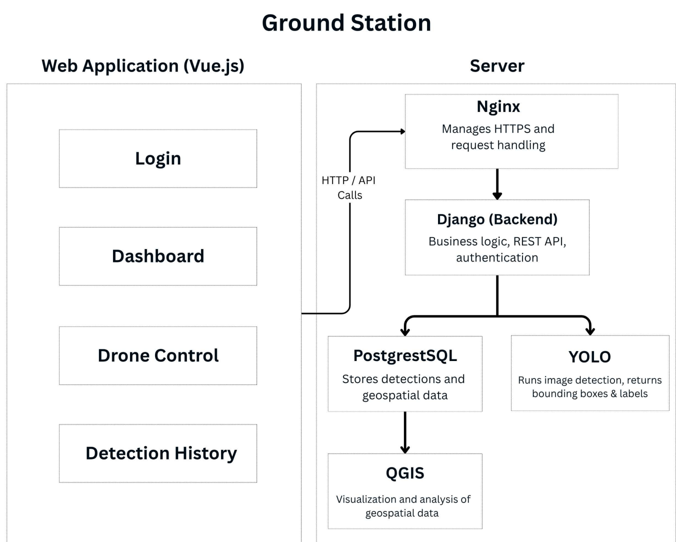
The results are immediately processed for both storage and visualization. A track log record is created and written to the database. Simultaneously, the system streams overlay frames to a website, updates real-time counters for healthy versus diseased pods, and refreshes map markers. This cycle repeats continuously as long as the mission remains active; once the mission is deactivated, the system executes the end mission sequence.

3.6.3 Ground Station Architecture

Figure 3.8 presents the entire system that manages the processing of UAV data and delivers results to the end user.

Figure 3.8

Ground Station System Design and Workflow



The Ground Station serves as the central control and processing hub of the proposed system, responsible for handling all backend operations, data management, and user interaction. It functions as the bridge between the UAV and the end user by receiving aerial images, processing them through the detection pipeline, and displaying the analyzed results through an accessible interface. Essentially, the Ground Station ensures that raw UAV data is transformed into actionable information, facilitating efficient monitoring, analysis, and decision-making for cacao pod disease detection in real time. It is composed of two closely connected parts: the web application and the server components.

The web application, developed in Vue.js, serves as the main user interface, providing modules for authentication, drone mission control, and visualization of detection outputs. The dashboard summarizes key statistics such as the number of pods identified as healthy or infected, while the history module allows users to review past detections and track trends over time, enabling farmers to monitor crop health and make informed decisions.

The server side of the Ground Station integrates several core technologies. Nginx acts as the web server and reverse proxy, handling HTTPS traffic and routing requests. Django functions as the application server, implementing the system's logic, managing authentication, and exposing a REST API for the web application. The detection process is carried out by the YOLO module, which receives aerial images and returns bounding boxes, labels, and confidence scores. Finally, PostgreSQL, extended with geospatial capabilities, stores the detection results along with their associated GPS coordinates. This allows the system to perform spatial queries and display disease distribution on a map. QGIS connects to the PostgreSQL/PostGIS database to visualize and analyze these spatial results, providing an advanced geospatial analysis platform for validating detections and generating detailed maps.

The operational workflow begins when images captured by the UAV are transmitted to the Ground Station. Django submits the images to the YOLO detection module and then attaches geospatial information derived from the UAV's GPS data. These enriched results are stored in PostgreSQL and subsequently retrieved by the web application for display. QGIS also retrieves this geospatial data directly from PostgreSQL to produce interactive maps and conduct further spatial assessments of the detected crop conditions.

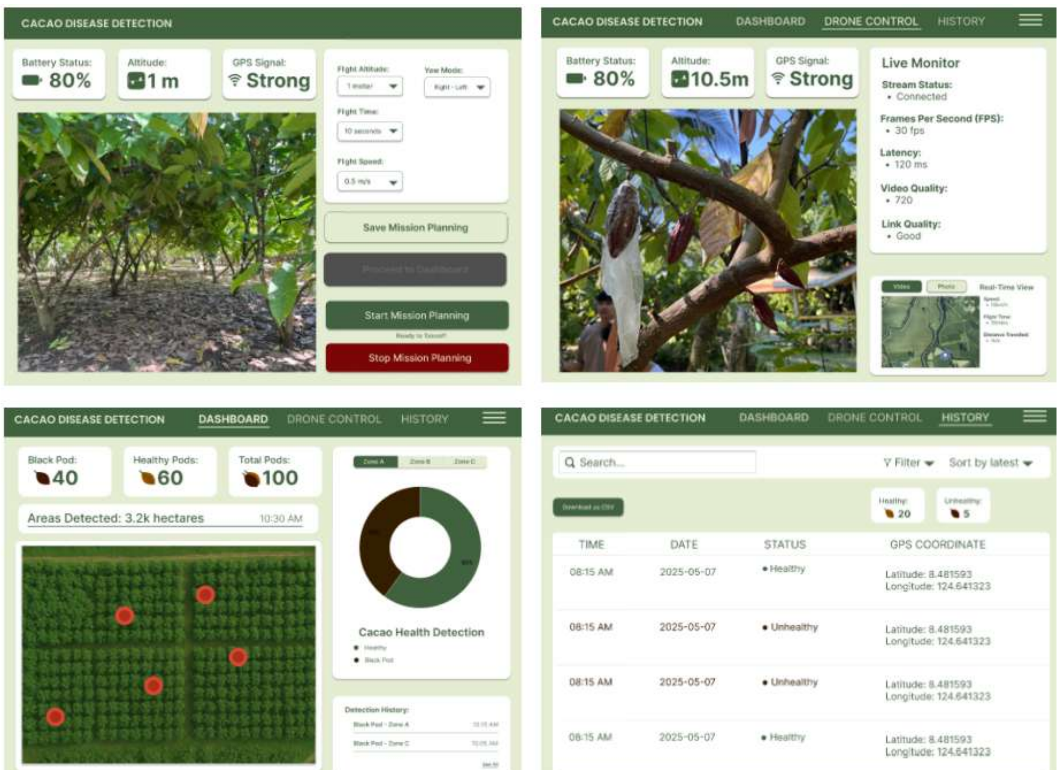
3.6.4 Graphical User Interface Design

The Graphical User Interface (GUI) of the Ground Station was developed to provide farmers and system operators with an accessible and practical platform for cacao disease monitoring. Based on the implemented web interface, the system is organized into four main pages—Dashboard, Mission Planning, Drone Control, and History—designed to support a complete workflow from mission setup, to real-time UAV monitoring, to reporting. The Dashboard presents an overview of detection results and coverage summaries, the Mission Planning page allows operators to configure flight parameters prior to deployment, the Drone Control page supports live streaming and real-time monitoring during flight, and the History page consolidates completed missions into a report for review and record keeping.

Figure 3.9 presents the web-based graphical user interface (GUI) of the ground station for cacao disease monitoring.

Figure 3.9

Web Application GUI



The interface is organized into multiple pages that support mission configuration, live UAV operation, visualization of detection results, and archival review of past missions. The Mission Planning page is used to configure flight parameters before deployment. It displays basic UAV status indicators (e.g., battery level, altitude, GPS signal) and provides adjustable mission settings such as flight altitude, yaw mode, flight speed, and capture or flight interval.

It also includes mission control actions (e.g., save mission plan, start mission, stop mission) to ensure systematic and repeatable flight execution along cacao rows.

The Drone Control (Live Monitor) page provides real-time operational monitoring during flight. It displays the live video stream together with the detection overlay produced by the model, including bounding boxes, class labels, and confidence scores. This page also presents stream health indicators such as connection status, frames per second (FPS), latency, video quality, and link quality, allowing the operator to assess streaming stability while operating the UAV.

The Dashboard page serves as the main results overview. It summarizes detection outputs through healthy and infected pod counts, total pod counts, and estimated area covered. It also includes zone-based views and visual summaries such as charts and map-style markers, enabling the user to quickly interpret the current crop health status and identify areas that require attention.

The History page provides an archive of previous detection missions and results. It includes search, filtering, sorting, and export functions (e.g., CSV download) and displays recorded entries with timestamps and detection status. When integrated with location data, the history records can also include GPS coordinates and related evidence frames to support traceability, repeat monitoring, and review of disease progression over time.

3.6.5 YOLOv11-Based Detection Implementation

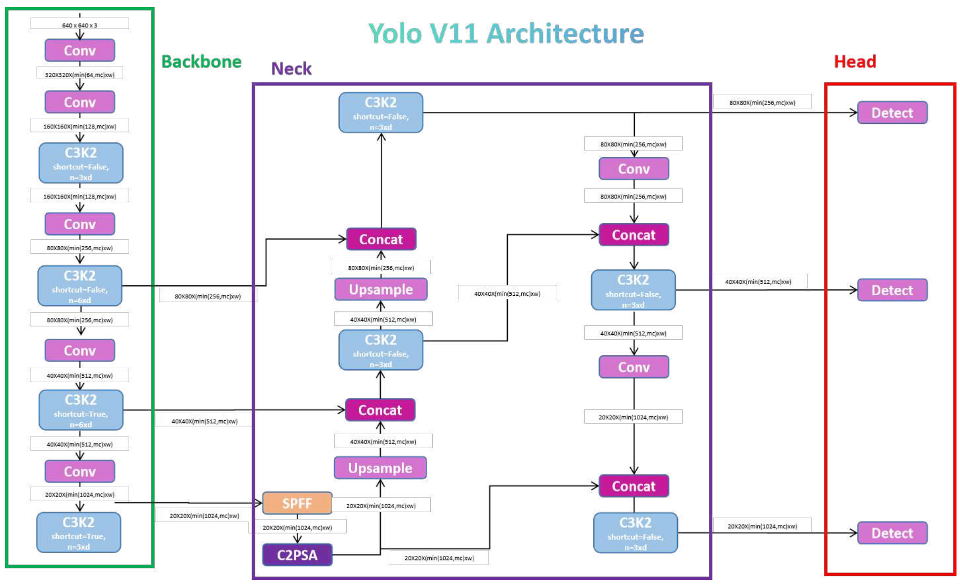
YOLO (You Only Look Once) algorithm, a CNN-based object detection framework that employs Convolutional Neural Networks to simultaneously determine the location of objects within an image and classify them. Unlike traditional image classification models, which merely indicate the presence of an object, YOLO predicts both what the object is and where it is situated by drawing bounding boxes around it in a single processing step.

YOLOv11 is employed since it introduces architectural improvements in feature extraction, particularly for small-object detection, and achieves higher accuracy with fewer parameters compared to earlier versions. YOLOv11 also provides scalable model variants that allow researchers to balance accuracy and computational requirements, making it highly suited for UAV-captured aerial imagery where cacao pods may appear small, numerous, and partially obscured.

Figure 3.10 shows the backbone for feature extraction, the neck for aggregating multi-scale feature maps, and the detection head outputs used for classifying and locating objects at various scales.

Figure 3.10

Architecture of YOLOv11, showing backbone with new C3K2 blocks, attention modules (C2PSA), Spatial Pyramid Pooling Fast (SPFF), and multi-scale detection heads (adapted from Khanam and Hussain, 2024)



The Intersection over Union (IoU) metric will be used to evaluate the model's ability to detect diseased cacao pods by measuring the overlap between predicted and ground-truth bounding boxes. It was chosen because IoU is known to be widely accepted standard for assessing YOLO-based object detection tasks. While it measures the overlap, combining it with precision, recall, and mean Average Precision (mAP) will provide a better testing metrics for the model performance.

Dataset Collection Method

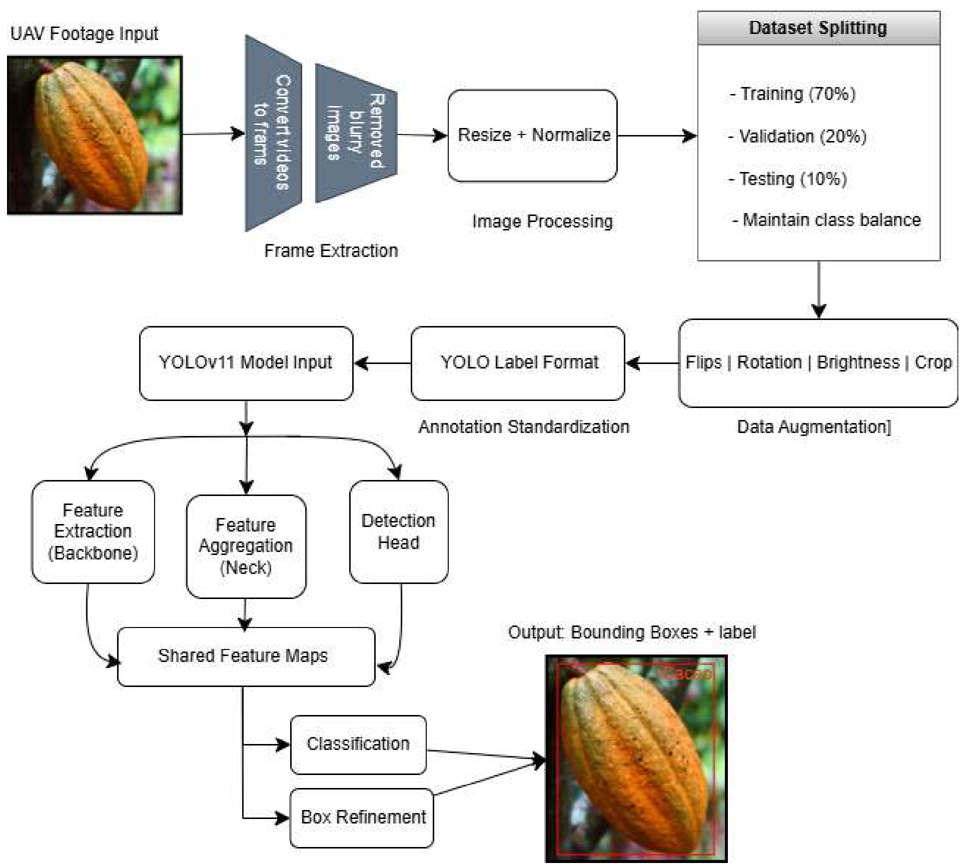
The dataset for this study will consist solely of a custom image dataset captured using a DJI RoboMaster TT's built-in camera during scheduled flights over cacao plantations. Images will be collected at multiple viewing angles and flight altitudes to capture variations in pod orientation, scale, and perspective. To improve robustness under real field conditions, the dataset will intentionally include healthy and diseased cacao pods across diverse illumination levels (e.g., shaded canopy vs direct sunlight), weather-related appearance changes, and natural background clutter. Particular focus will be placed on documenting multiple stages of infection and varying degrees of pod occlusion by leaves, branches, or neighboring pods. All captured images will be manually annotated to label the regions of interest, providing the ground-truth required for supervised training of the YOLO model.

Data Preprocessing

As shown in Figure 3.11, the process begins with raw imagery collected through Unmanned Aerial Vehicles (UAVs) and external datasets. The UAV-captured videos are converted into individual frames at fixed intervals, ensuring that every pod instance is represented across varying viewpoints. Blurry, redundant, or low-quality frames are systematically removed to eliminate noise and improve dataset consistency. The selected images are resized and normalized according to YOLOv11's input dimensions (e.g., 640×640 pixels), preserving the aspect ratio to prevent geometric distortion. Normalization scales pixel values into a uniform range (typically 0–1) to enhance computational efficiency and model stability.

Figure 3.11

Workflow of the YOLOv11-based cacao disease detection system, showing data preparation, model input, and classification outputs.



The curated dataset is then divided into training, validation, and testing subsets, often following a 70–20–10 ratio. This split ensures balanced class representation and prevents overfitting by maintaining a consistent ratio of healthy and diseased pods across subsets. Data augmentation is applied exclusively to the training set to simulate real-world variability and improve the model's generalization. Transformations such as random horizontal and vertical flips, rotations, brightness and contrast adjustments, and cropping expose the model to different illumination, orientation, and scale conditions. All annotations are standardized into the YOLO label format, which specifies object class IDs and bounding box coordinates in normalized values. This standardized structure ensures seamless integration with YOLOv11's training and detection pipeline, enabling the model to correctly interpret positional and categorical information during learning.

Cacao and Disease Detection

The UAV-captured cacao images are fed into the YOLOv11 model for automated object detection and disease classification. YOLOv11 divides each image into a predefined grid structure, where each grid cell predicts multiple bounding boxes, corresponding confidence scores, and class probabilities. This design allows the model to simultaneously identify multiple cacao pods within a single frame, efficiently localizing each pod even under challenging conditions such as dense foliage, overlapping objects, or inconsistent lighting. Detected pods are enclosed within bounding boxes that represent the system's prediction of their exact position within the image.

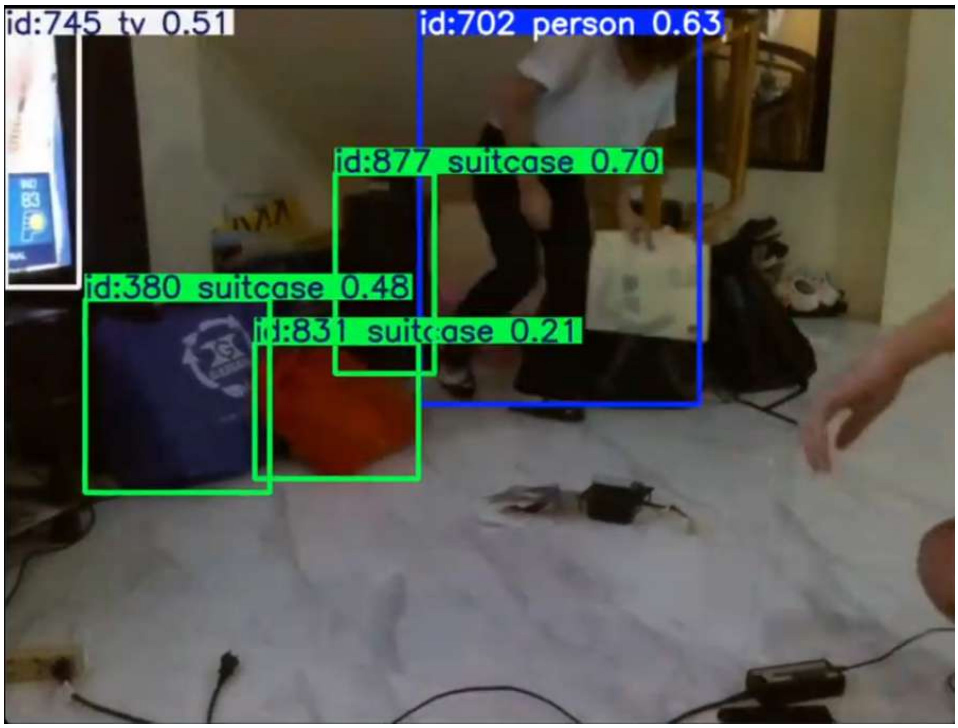
Once localization is complete, YOLOv11 proceeds with the classification of each detected pod as either healthy or infected with black pod disease. This classification is based on visual patterns learned during model training, including texture irregularities, surface discoloration, dark lesions, and other symptoms characteristic of infection. The model leverages deep feature extraction through its backbone network, multiscale feature fusion in the neck, and final detection through its head architecture. The output consists of annotated images displaying bounding boxes and class labels, where healthy pods are distinctly marked from diseased ones. This end-to-end workflow enables precise, efficient, and scalable cacao pod monitoring, facilitating early detection and management of black pod disease in agricultural environments.

Real-Time Processing, Detection, and Result Output

Real-time processing and real-time detection will be performed during UAV flight by executing the detection pipeline on the ground station immediately as frames are received from the live video stream. Each incoming frame will undergo lightweight, per-frame standardization before inference, including color format conversion, letterbox resizing to the model input size, and pixel normalization. The standardized frame will then be forwarded to YOLOv11 to generate detections consisting of bounding boxes, class labels, and confidence scores. Detection results will be displayed immediately through on-screen overlays on the ground station for monitoring and verification, and detection logs will be written concurrently with timestamps and available location metadata to support live reporting. Under this workflow, continuous video will not be archived; instead, only detection outputs and selected evidence frames will be retained to minimize storage requirements while preserving traceability of reported detections.

Figure 3.12

Sample real-time detection output from the UAV video stream on the ground station using ByteTrack.



Object Tracking and Duplicate Suppression

To avoid counting the same cacao pod multiple times across consecutive frames, an object tracking mechanism will be integrated using ByteTrack. For each incoming frame, YOLOv11 produces bounding boxes, class labels, and confidence scores. These detections are then forwarded to ByteTrack, which associates detections across frames and assigns a persistent track ID per pod. A pod will be recorded as a unique instance only once per track ID within a defined time window, while subsequent detections of the same track will be treated as the same pod.

To further reduce duplicate records under rapid camera motion or unstable tracking, an Intersection-over-Union (IoU) consistency check will be applied between consecutive bounding boxes of the same track ID. When the IoU falls below a defined threshold, the detection will be treated as a movement/instability event and will require additional confirmation across subsequent frames before being logged as a valid record. This combined tracking and IoU-based consistency filtering reduces duplicate logs caused by camera motion, overlapping views, or repeated observation of the same pod during flight, improving the reliability of pod counts and geo-tagged reports.

Visual and Object Geo-localization

The UAV is equipped with a GPS module and a forward-facing camera that captures images of the cacao pods during flight. Each image is associated with the DJI RoboMaster TT's GPS at the moment of capture. The images are then processed using an object detection model (YOLOv11), which generates bounding boxes around identified cacao pods. A bounding box is defined by its pixel coordinates (x, y, w, h), where (x, y) is the top-left corner, and w and h are the width and height in pixels.

To estimate whether the drone's GPS can be used as an approximate location for a cacao pod, we use the size of the pod's bounding box in the image together with the camera's field of view and image resolution. This idea comes from Leorna et al. (2022), which uses the pinhole camera model, that relates an object's real-world width, its distance from the camera, and its size in pixels. First, the researchers computed the camera's focal length in pixels using the formula

$$f = \frac{\text{image width in pixels}}{2\tan(\text{HFOV}/2)}, \tag{1}$$

where $HFOV$ is the horizontal field of view in radians. The DJI RoboMaster TT has a 5 MP image (2592 pixels wide) with a horizontal FoV of 82.6°. This gives a focal length of approximately 2620.45 pixels. The calculated pixel-width threshold for the cacao pod is

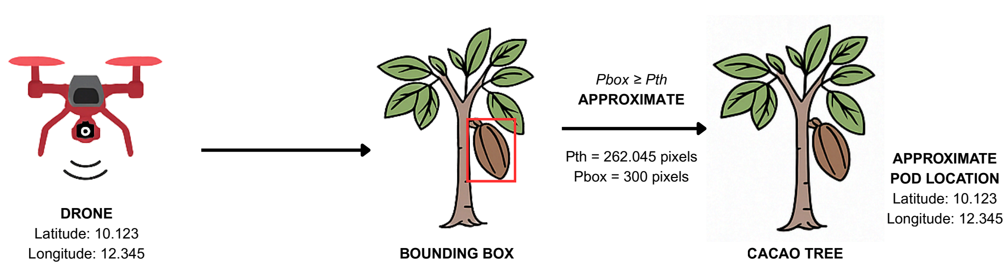
$$P_{\text{th}} = \frac{W \cdot f}{D_{\max}}, \tag{2}$$

where W is the real width of the pod (e.g., 0.10 m) and $D_{\max}$ is the maximum distance from the drone at which we are willing to accept its GPS as an approximate pod location (e.g., 1.0 m). Using these numbers, the threshold is about 262.045 pixels, calculated from eq. (2) (Leorna et al., 2022). This means that any cacao pod whose bounding box width is equal to or greater than 262.045 pixels is close enough that the drone's GPS can be used as an approximate pod location, while smaller bounding boxes correspond to pods that are farther away and whose GPS positions would be inaccurate.

As shown in Figure 3.13, the pod has bounding box with 300 pixels widths greater than the threshold (262.045 pixels) are close enough that the drone GPS can be used as an approximate pod location, while smaller boxes correspond to pods that are farther away.

Figure 3.13

Tree Geolocalization



3.6.6 UAV Drone System

The DJI RoboMaster TT (Tello Talent), a programmable quadcopter equipped with a Vision Positioning System, a 5 MP camera, and an expansion kit for modular extensions. Figure 3.14 shows an image of DJI RoboMaster TT. It was chosen for its lightweight design, stability at low altitudes, and compatibility with open-source programming platforms.

Figure 3.14

DJI RoboMaster TT UAV

The RoboMaster TT integrates several important functions. Its flight system combines a flight controller and propulsion motors with the Vision Positioning System (VPS), which uses a downward-facing camera and infrared sensors to maintain stable hovering at low altitudes without relying on GPS. This feature is essential for operating indoors or close to the ground, such as at eye level within cacao plantations.

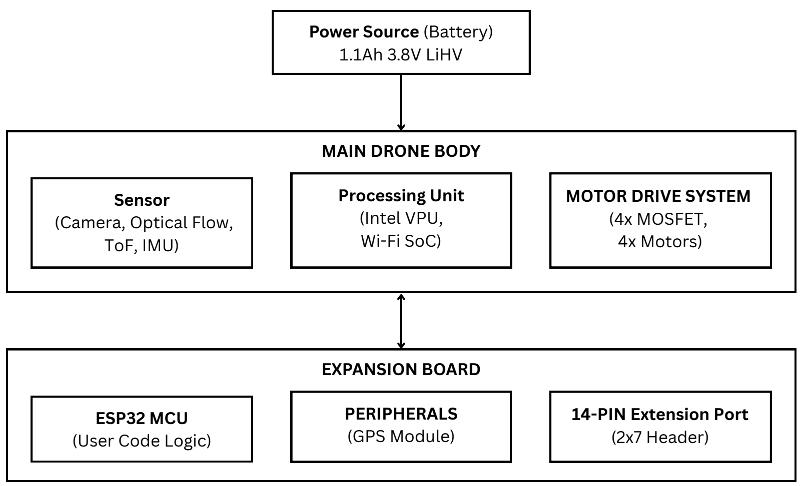
The onboard 5 MP camera enables the capture of still images and 720p HD video, suitable for documenting cacao pods. Power is supplied by a 3.8 V, 1100 mAh LiPo battery, supporting flight times of up to 13 minutes. Safety features include propeller guards, battery protection, and automatic landing in case of weak signals or low power. The expansion kit includes an ESP32-

based open-source controller, providing UART, I2C, GPIO, PWM, and SPI interfaces for integrating additional modules such as the GPS receiver.

The RoboMaster TT integrates several important functions, as illustrated in the system block diagram in Figure 3.15. Its flight system combines a flight controller and propulsion motors with the Vision Positioning System (VPS).

Figure 3.15

System Block Diagram of the DJI RoboMaster TT



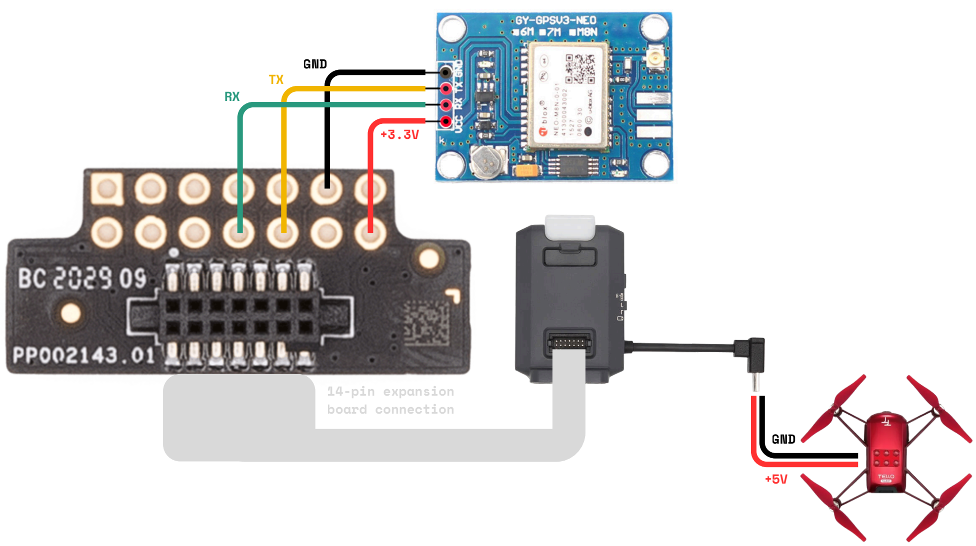
The onboard 5 MP camera enables the capture of still images and 720p HD video, suitable for documenting cacao pods. Power is supplied by a 3.8 V, 1100 mAh LiPo battery, supporting flight times of up to 7 minutes. Safety features include propeller guards, battery protection, and automatic landing in case of weak signals or low power. The expansion kit includes an ESP32-

based open-source controller, providing UART, I2C, GPIO, PWM, and SPI interfaces for integrating additional modules such as the GPS receiver.

Figure 3.16 illustrates the hardware interfacing between the RoboMaster TT's expansion board (ESP32 Controller) and the external NEO-M8N GPS module via the Universal Asynchronous Receiver-Transmitter (UART) protocol.

Figure 3.16

Expansion Board Circuit Diagram



The GPS module is powered by the 3.3V output from the expansion board, with a common Ground (GND) connection ensuring signal stability. Data communication follows a cross-coupled configuration where the GPS TX (Transmit) pin connects to the ESP32 RX (Receive) pin to stream NMEA data containing geospatial coordinates. Conversely, the GPS RX pin connects to the ESP32 TX pin, allowing the controller to send configuration commands to the module. This direct UART connection enables the ESP32 to parse geospatial data with low latency, which is then synchronized with the video feed for the telemetry overlay.

Command-based Mission Control with RoboMaster TT SDK

The Software Development Kit (SDK) enables command-based mission planning with the DJI RoboMaster TT. Through the SDK, the drone executes scripted flight commands such as `takeoff`, `forward(x)`, `back(x)`, `cw(angle)`, and `land`, allowing it to follow predefined flight paths across cacao rows. During these missions, the drone captures images of cacao pods at specific intervals, paired with location data provided by the integrated NEO-M8N GPS module.

An offline detection approach was adopted: the collected images and GPS coordinates are stored and later processed using the YOLO algorithm. The results of detection are then mapped in QGIS to identify and visualize areas affected by *Phytophthora palmivora*. This workflow synchronizes drone navigation, image acquisition, and geotagging while accounting for the hardware limitations of the RoboMaster TT.

GPS Integration and Data Handling

A NEO-M8N GPS module was connected to the open-source controller via UART for geolocation. The NEO-M8N is a high-performance GNSS receiver capable of tracking multiple satellite systems (GPS, GLONASS, Galileo, and BeiDou). It provides efficient position, velocity, and time data, which were synchronized with each captured image to create geotagged datasets. This integration enabled the precise mapping of cacao pods and potential disease symptoms in QGIS.

All communications between the UAV and the ground station were established through a Wi-Fi connection. The SDK relies on UDP packets transmitted over Wi-Fi to send flight commands and receive status updates. For structured telemetry such as GPS coordinates and mission logs, the MQTT protocol was integrated as a lightweight messaging layer, ensuring reliable delivery of small data packets. Image files, due to their larger size, were transferred directly via the Wi-Fi link to the ground station.

After each mission, the drone transmitted images and GPS logs to a central database. The ground station retrieved these records from the database for preprocessing and analysis. This workflow ensured that raw images and geospatial metadata were securely stored and easily accessible for the YOLO-based detection system and subsequent spatial visualization in QGIS.

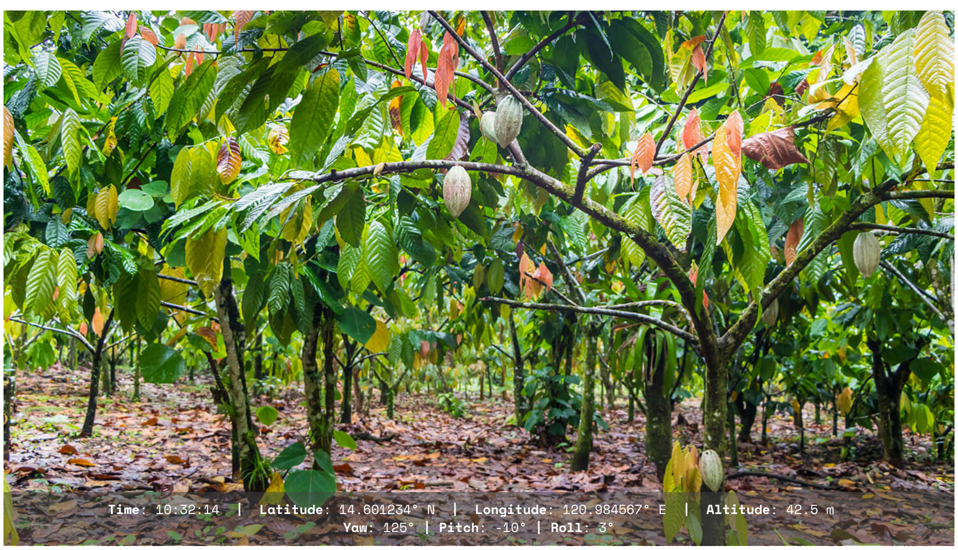
Telemetry Overlay

During flight, the UAV continuously records telemetry data consisting of timestamp, latitude, longitude, altitude, and orientation parameters (yaw, pitch, and roll). These telemetry values are synchronized with the video stream and image frames, ensuring that every recorded frame has an associated spatiotemporal context for efficient tracking.

Telemetry overlay, as shown in Fig. 3.17, refers to the process of superimposing flight data directly onto the visual feed or processed image output.

Figure 3.17

Telemetry Overlay



This provides operators with real-time situational awareness and enables more precise post-flight analysis. Telemetry overlay displays the UAV's recording time, positional coordinates, altitude, and orientation alongside the YOLOv11 bounding boxes of detected cacao trees. It helps users quickly interpret both detection and flight information together. This integration ensures that detections are not only localized within an image but also connected to the UAV's position and state during capture.

The inclusion of telemetry information serves multiple functions. (1) The timestamp allows for chronological indexing of detections, supporting analysis of cacao disease monitoring. (2) The geographic coordinates (latitude, longitude, altitude) provide a direct spatial reference to the UAV's position during detection. (3) The IMU-derived orientation (yaw, pitch, roll) supplies critical context on the UAV's attitude, which can affect the angle and scale of captured images.

Together, these parameters create a transparent record of the flight path and its associated detections, enabling efficient mapping, post-flight analysis, and data validation.

3.6.7 Materials and Cost

Table 3.2

Components and Cost

Component	**Price (₱)**
Drone (DJI RoboMaster TT)	20,000.00

Component	Price (₱)
NEO-M8N GPS module	300.00
Total Cost	**20,300.00**

3.7 Test and Evaluation

Testing will be conducted to ensure that the system will operate efficiently, and be suitable for real-world use in cacao farm management. The process will involve functional testing, usability testing, and performance testing. Functional testing will verify whether key features such as UAV image capture, detection of Phytophthora palmivora-infected cacao pods using YOLO, and geotagging of infected trees perform as intended, with each function tested through defined inputs and expected outputs. Usability testing will assess how easily end users, particularly cacao farmers, can navigate and interact with the system by performing essential tasks such as logging in, accessing detection results, and interpreting geotagged maps. Feedback will be collected using the System Usability Scale (SUS) to evaluate the overall user experience. Performance testing will measure 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 will validate the system's reliability, user-friendliness, and effectiveness in supporting early disease detection and timely intervention.

3.7.1 Functional Testing

Functional testing will be carried out to ensure that every part of the system will work 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 providing specific inputs and checking if the outputs match the expected results.

3.7.2 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.

Performance Testing

Performance testing will be conducted to evaluate the system's responsiveness, accuracy, and overall reliability based on its core functionalities. This will include measuring the accuracy of detecting Phytophthora palmivora infected cacao pods using the YOLO, assessing the precision of geolocation through the GPS module and QGIS, and recording the system's response time from image capture to the display of results on the dashboard. The testing will also evaluate the system using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, and Error Rate to determine the effectiveness of the detection model. These evaluations will verify whether the system will meet its intended performance criteria and will be capable of supporting timely and informed decision-making in cacao disease management.

Table 3.3

Performance Metrics for Cacao Pod Detection

Metric	**Equation**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-Score	$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$

Metric	Equation
Error Rate	$\frac{FP + FN}{TP + TN + FP + FN}$

Table 3.3 presents the performance metrics used to evaluate the cacao pod detection system. Accuracy measures the overall correctness of the system by calculating the proportion of correctly classified instances, including both infected and healthy pods, out of the total number of samples. Precision indicates the proportion of pods identified as infected that are actually infected, which is important to minimize false positives. Recall measures the proportion of actual infected pods that the system correctly identifies, ensuring that most infected pods are detected. The F1-Score provides a balance between precision and recall by calculating their harmonic mean, which is particularly useful when both false positives and false negatives need to be minimized.

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APPENDICES

APPENDIX A

LETTER OF CONSENT

UNIVERSITY OF SCIENCE AND TECHNOLOGY OF SOUTHERN PHILIPPINES
Alubijid | Cagayan de Oro | Claveria | Jasaan | Oroquieta | Panaon

INFORMED CONSENT

I ________________________, hereby consent to participate/ be a respondent in this research titled: "*Automated Black Pod (Phytophthora Palmivora) Disease Detection in Cacao Pods using UAV*"

I am aware that I should keep a copy of the Letter of Introduction and Consent Form for future reference

I understand that:

I am free to withdraw from the participation in this research at any time and I am free to refuse to answer particular questions

While the information gained in this study will be published as explained, I will not be identified, and individual information will remain confidential.

Data from this research will be kept under lock and key and reported only as a collective combined total. No one other than the researchers will know my individual answers to their questionnaire.

Participant's Name/Signature: ______________ Date: ______________

I certify that I have explained the purpose of the research to the participant and consider that he/she/they understands what is involved and liberally consents to participate.

Very truly yours,

Novem Kate Barbosa
Thesis Leader

Jason T. Daohog
Thesis Researcher

John Patrick L. Rautraut
Thesis Researcher

Joel F. Sabuero Jr.
Thesis Researcher

Jeushian Ritz Reblando
Thesis Researcher

UNIVERSITY OF SCIENCE AND TECHNOLOGY OF SOUTHERN PHILIPPINES
Alubijid | Cagayan de Oro | Claveria | Jasaan | Oroquieta | Panaon

September 26, 2025

Engr. Jodie Rey Fernandez
Thesis Adviser
Department of Computer Engineering
University of Science and Technology of Southern Philippines

Dear Engr. Fernandez,

Good day!

We, the undersigned researchers of the study entitled "*Automated Black Pod (Phytophthora Palmivora) Disease Detection in Cacao Pods using UAV*", respectfully submit our Pre-Survey Interview Questionnaire for your review and validation.

The purpose of this questionnaire is to gather the necessary preliminary information that will serve as a basis for our main survey and strengthen the reliability of our study. We humbly request your evaluation regarding the clarity, relevance, and appropriateness of the questions to ensure that they align with the objectives of our research.

Your expertise and guidance will greatly help us refine our instrument and guarantee that it is valid for use in data collection.

Thank you very much for your time and support. We look forward to your feedback and recommendations.

Respectfully yours,

Novem Kate Barbosa
Thesis Leader

Jason T. Daohog	**John Patrick L. Rautraut**	**Joel F. Sabuero Jr.**	**Jeushian Ritz Reblando**
Thesis Researcher	Thesis Researcher	Thesis Researcher	Thesis Researcher

Noted by:

Engr. Jodie Rey Fernandez
Thesis Adviser

APPENDIX B

INTERVIEW CONDUCTED

Interviewer(s)	Jason T. Daohog / Jeushian Ritz Reblando / Novem Kate Barbosa
Note Taker	John Patrick Rautraut
Observer	Joel F. Sabuero Jr.
Location	Janog Cacao Plantation, Initao, Misamis Oriental
Date: 10-5-2025	**Start Time:** 1:30 PM **End Time:** 4:00 PM
Objectives	To understand existing farming practices, identify challenges in disease detection and management, and collect essential information for system development.

Name (Ngalan) (optional): **Erlinda Janog**
Age (Edad):

1. How big is your cacao farm?
Pila kadako imong umahan sa kakaw? (sa hectares o square meters)
5 hectares

2. Does the size make your work harder or easier each day?
Ang kadako ba sa imong uma makapadali o makalisod sa imong trabaho adlaw-adlaw?
It makes the work harder since the area is large, and it takes more time to check all trees and manage spraying or pruning

3. How do you usually enter your farm when you check the trees? (by road, by foot, etc.)
Giunsa nimo kasagaran pag-agi sa umahan kung mag-inspeksiyon ka sa mga kahoy?
By foot

4. What problems do you face when going around your farm?
Unsa nga mga problema imong makita kung mubisita ka sa uma?
Spray, pruning, danggan, rain

5. Are there things like tall trees, hills, rivers, or power lines in or near your farm?

Naa bay mga taas nga kahoy, bungtod, sapa, o mga kuryente nga linya sa sulod o duol sa umahan?
Yes

6. How do these affect your work with the cacao trees?
Pa-unsa ni siya naka-apekto sa imong pagtrabaho sa umahan?
No

7. What is the first thing you see when a cacao pod is diseased? (color, spots, wilting, etc.)
Unsay unang butang nga imong makita kung ang bunga sa kakaw kay naay daut? (kolor, naay mansa, ug uban pa)
Appearance

8. What signs do you look for before you say a cacao is unhealthy?
Unsa ang mga timailhan nga imong tan-awon una kung ang kakaw kay daut?
Color dots, phytophthora

9. How do you remember which tree has a diseased cacao? (notebook, marking, memory, etc.)
Giunsa nimo paghinumdom kung asa nga mga kahoy ang naay daut nga kakaw? (notebook, marka, hinumdoman ra, ug uban pa)
The affected tree won't affect another tree. It will only affect the pods in that affected tree

10. When you see a diseased cacao pod, what do you do first? (cut, spray, remove, etc.)
Kung makakita kag bunga sa kakaw nga daut, unsa imong buhaton una? (putlon, sprayan, tangtangon, ug uban pa)
Spray, unnoticed due to other

11. Which methods work best for you to control disease?
Unsa ang mga pamaagi ang mas epektibo para nimo aron makontrol ang daut?
Pest control spray

12. Which ones do not work well?
Unsang mga pamaagi ang dili kaayo epektibo?

Wrapping pods with plastic during the rainy season, since it causes mold formation.

13. How do you decide if you will treat, cut, or remove the sick pod?
Giunsa nimo pagpili kung tambalan, putlon, o tangtangon ang daut nga bunga?
Remove only

14. How many times do you check your cacao for disease? (per week or per month)
Kapila ka mag-inspeksiyon sa mga daut na kakaw? (kada semana o kada bulan)
Everyday (3 weeks per area)

15. Do you check more often in the rainy or dry season?
Mas kanunay ba ka mag-inspeksiyon sa ting-uwan o sa ting-init?
Both. Especially during rainy seasons, each pod should not be wrapped in a plastic since it will mold except for those who are already wrapped

16. What problems do you face when checking your cacao for disease?
Unsa nga mga problema imong naagian kung mag-inspeksiyon ka sa mga daut nga kakaw?
Sometimes it's hard to see the pods because of the rain and thick leaves.

17. Can you tell a story when you found a disease too late?
Pwede nimo mahulagway pag diskobre nimo nga ulahi na nakita nga daut ang kakaw?
It happened during the rainy days when I couldn't check the trees. When I came back, some of the pods were already black and rotten

18. What happened to your harvest after that?
Unsay nahitabo sa imong ani pagkahuman ato?
Harvest 5-7 kilo (Peak season duing november to december)

Documentation: