POLYTECHNIC UNIVERSITY OF THE PHILIPPINES

Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (*Mangifera indica* L.) Leaves

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THE PROBLEM AND ITS SETTING

Introduction

The Philippine mango industry, long regarded as a global producer of premium-quality mangoes, plays a significant role in the country's agricultural sector and export economy. In 2020, it contributed PhP 35.52 billion in gross value added and remained the third most exported fruit crop in the country (Department of Agriculture - Bureau of Agricultural Research, 2022). Among the country's three well-known varieties, Carabao, Pico, and Katchamita (Indian mango), the Carabao mango (*Mangifera indica* L.) stands out as the most cultivated and economically important variety. Known as the world's sweetest mango, it accounts for about 80% of national mango production and is the main driver of both domestic supply and export demand. Despite its importance, the industry has been in a continuous decline, with reductions in production volume, productive area, and yield per unit area. A major driver of this decline is the prevalence of pests and diseases, among which anthracnose has been identified as the most serious fungal disease affecting mango production and postharvest quality (Department of Agriculture – Bureau of Agricultural Research, 2022).

Anthracnose, caused by *Colletotrichum gloeosporioides*, severely affects mango leaves, flowers, and fruits, leading to reduced tree vigor, blossom blight, fruit rot, and even total crop failure. Yield losses attributed to anthracnose can reach 30 to 60% annually, with reports of up to 100% loss in unmanaged plantations (Dofuor et al., 2023; Asmita et al., 2022). Since anthracnose infection often remains latent until fruit maturity or postharvest, traditional visual inspection fails to detect it at an early stage when interventions would be most effective (Dofuor et al., 2023). As a result, infected fruit can still enter the food chain before the infection is known (Ubonrat Siripatrawan & Makino, 2023). In the Philippines, anthracnose and stem-end rot are the leading causes of pathological damage in mangoes from major producing provinces such as Iloilo and Guimaras (Galvan, 2024). This postharvest vulnerability not only reduces marketable yield but also limits the country's competitiveness in international markets where higher quality standards are required.

Current management strategies, such as the application of synthetic fungicides and hot water treatment (HWT), have significant limitations that prevent them from fully addressing the problem. While fungicides can be effective, their overuse has led to the emergence of resistant fungal strains and concerns over chemical residues and environmental pollution (Ciofini et al., 2022; Rattanakreetakul et al., 2023). HWT, a non-chemical method, is not widely adopted by local farmers due to its high cost, time requirements, and limited economic incentives in the local market (Department of Agriculture - Bureau of Agricultural Research, 2022). These persistent challenges underscore a critical need for a practical, cost-effective, and sustainable solution for early disease detection and management.

Emerging technologies in agricultural automation offer a promising path forward for improving disease management and productivity in the mango industry. The traditional process of manual inspection is labor-intensive, time-consuming, and prone to inefficiency, resulting in significant production and profit losses (Joshi et al., 2024; Kumar et al., 2025). In response to these challenges, Computer Vision (CV) systems have become a cornerstone of smart agriculture. These systems utilize algorithms to interpret images and provide non-contact, efficient, and data-driven solutions for various agricultural activities, including plant health analysis (Dhanya et al., 2022). At the heart of CV's success is Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), which have proven to be the leading architectures for image classification, object detection, and semantic segmentation in agricultural applications (Zhao et al., 2024; Dhanya et al., 2022).

Deep learning models have demonstrated remarkable success in the detection and severity estimation of mango diseases, offering significant advantages in both speed and accuracy (Mir et al., 2024). For classifying the severity of plant diseases, CNNs and hybrid models that combine CNN feature extraction with traditional classifiers such as Support Vector Machines (SVM) or Random Forest have shown exceptional effectiveness (Kaur et al., 2024; Panuganti, 2024; Mir et al., 2024). In the context of mango leaf diseases, studies utilizing advanced Convolutional Neural Network (CNN) architectures have demonstrated exceptional classification performance. For instance, ResNet50 has exhibited unparalleled accuracy, reaching as high as 99.12% in identifying various mango leaf diseases (Bairwa et al., 2024), and up to 100% when integrated into a hybrid model alongside EfficientNetB1 (Shweta Bhattacharjee Porna et al., 2024). Furthermore, hybrid approaches leveraging VGG16 features with a Random Forest classifier have yielded high validation accuracies of 97.75% (Panuganti, 2024). Even for specialized tasks, lightweight models like the CBAM-DBIRNet, a double branch inverted residual attention network, achieved 98.42% accuracy in classifying anthracnose infection grades in natural environments (Zhang et al., 2025). These consistently high metrics, which often range from 97% to 99% or higher across different CNN and hybrid configurations, underscore the robustness of deep learning for accurate mango leaf disease diagnosis (Sandhya S et al., 2022; Banerjee & B. Swathi, 2025).These models have been developed not only for simple detection but also for accurately diagnosing the degree or severity of anthracnose on mango leaves and fruits, which is a crucial factor in effective disease management and protection (Mir et al., 2024; Zhang et al., 2025; Faye et al., 2025; Mehta et al., 2023).

The demonstrated success of CNN-based systems highlights a viable and practical approach to addressing the persistent challenges faced by the Philippine mango industry. Advanced CNN architectures, such as the lightweight CBAM-DBIRNet model, have achieved high accuracy (98.42%) in classifying anthracnose infection grades on mango leaves in complex natural environments while maintaining a compact model size suitable for real-time field deployment (Zhang et al., 2025). Building on this progress, the present study proposes the development of a CNN-based computer vision system for the automated, non-destructive detection and severity estimation of anthracnose in mango leaves. By offering a practical, cost-effective, and highly accurate field-based solution, this system aims to facilitate early disease management, improve fruit quality, and enhance the overall competitiveness of the Philippine mango industry.

Theoretical Framework

The theoretical foundation of this study lies in the principles of plant pathology and existing theories of computer vision that build up the foundation of the study. Modern agriculture applies primitive techniques of farming and novel advancements of technology, often known as precision agriculture. This diverse field is defined as a management approach that utilizes information technology to collect and analyze data from various sources to inform crop production decisions. Such a method involves identifying and measuring geographical and seasonal variations within agricultural sectors, enabling tailored agronomic treatments for specific sites (Peduruhewa et al., 2024). With this in mind, the detection of plant disease became one of the critical aspects of precision agriculture, particularly in regions where crops, such as mango, hold economic and cultural significance. With the advancement of computer vision (CV) and artificial intelligence (AI), automated plant disease detection systems are now feasible, offering rapid, consistent, and accurate results.

This study delves deeper into detecting Anthracnose disease on Mango leaves. More specifically, Mango Anthracnose Disease (MAD) is a destructive disease caused by the fungus *Colletotrichum gloeosporioides*. Typically, leaf dots usually appear close to the leaf's margins. They often have a deeper border and range in color from light tan to deep brown. The risk of infection rises when new leaf flushes appear during damp spells. These kinds of infections usually show up as semicircular lesions on the edges of young leaves that are pale green or golden. Extended exposure to excessive humidity may result in defoliation of young shoots and a black spot on freshly emerging branches. (Rezazadeh, 2023). Understanding the progression of MAD is important because early detection allows farmers to intervene before the disease severely damages crops, especially since MAD can cause a 100% loss of yield in orchards that are not well taken care of and where the environment is good for the disease to spread (Dofuor et al., 2023).

The call for precise agriculture pertaining to anthracnose detection supervised this study to apply deep learning and pattern recognition for such tasks. In such cases, the use of Convolutional Neural Networks (CNN) and Computer Vision (CV) are the main core components of the study. Firstly, computer vision posits that the world, as captured in 2D image, is mainly composed of structured and statistically regular visual patterns that a machine can learn to recognize. In a technical sense, computer vision is a field of artificial intelligence and computer science that enables machines to understand and interpret visual information from images and videos. It involves developing algorithms and techniques to extract meaningful insights, patterns, and knowledge from visual data, mimicking human visual perception capabilities (Pandey, 2023). Feature engineering plays a fundamental role in computer vision pipelines, contributing significantly to tasks such as object recognition, image retrieval, and image segmentation (Elhariri et al., 2021). Traditional approaches relied on handcrafted features like SIFT, SURF, HOG, ORB, LBP, and KAZE, which could be computed globally across entire images or extracted from local sub-regions and aggregated (Susan & Tuteja, 2024). These engineered features were then processed by classifier models for various applications. However, the field has witnessed a significant transition from traditional feature engineering to deep learning approaches, with deep convolutional neural networks and vision transformers now representing the current state-of-the-art in computer vision (Susan & Tuteja, 2024).

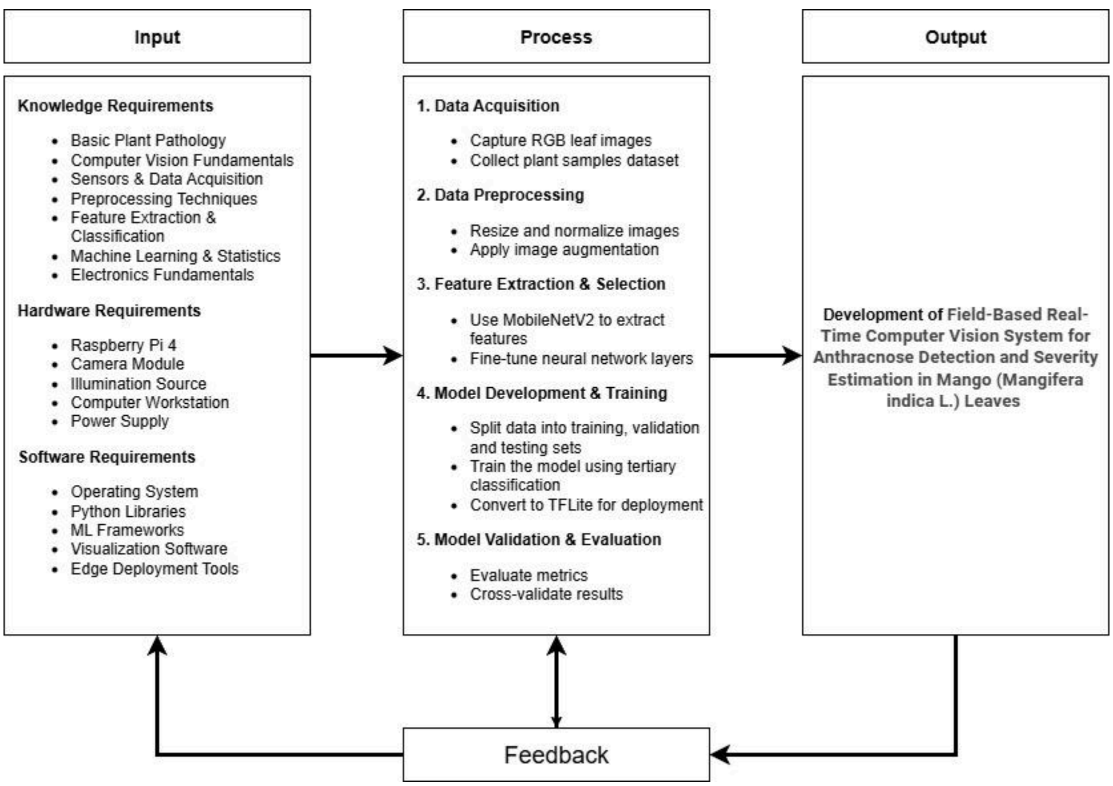
The introduction of deep learning, notably Convolutional Neural Networks (CNNs), is a paradigm shift, from hand-crafted feature engineering to automatically learned features, and this revolutionized image classification significantly. Convolutional Neural Networks (CNNs) are type-specific networks that were designed for the computation of the grid-like data structure, notably images as 2-D grids of pixels. Unlike standard neural networks, the CNNs work on 3-D data, i.e., height, width, and depth, and have layers that employ spatial structure, including convolutional layers, pool layers, as well as fully connected layers. In the convolutional layer, the filters, also called kernels, scan the input to compute dot products that extract pattern and features, where complexity is controlled through parameter sharing as well as hyperparameters like stride as well as padding. Pooling layers reduce the dimension as well as prevent overfitting, while the last fully connected layer performs the classification, typically through the softmax activation to output the probabilities of the classes. As the convolutional layers deepen, the early, mere features are accumulated into progressively more complex as well as abstract representations such as a circular lesion, necrotic tissue pattern, then the specific morphology of the anthracnose itself. This end-to-end, hierarchical feature acquisition is the core theoretical advantage over the traditional computer vision methodologies, which were compelled to be reliant on manual, expert feature engineering. Hence, this work directly leverages this theory idea to automatically acquire, through the use of a CNN-based structure like the MobileNetV2, a strong, hierarchical anthracnose symptom model directly off the pixels without making explicit use of the pre-specified feature extraction algorithms.

CNNs require large amounts of data and computational resources, making them challenging to implement on small datasets (Emmanuel & Onuodu, 2022; Khotsyanovsky, 2022). Transfer learning addresses these limitations by utilizing pre-trained CNN models and adapting them to new tasks. In this approach, the weights of pre-trained network layers are "frozen" except for the final fully connected layer, which is replaced with a new layer matching the number of target classes. This technique significantly reduces computational requirements and enables effective training on smaller datasets. Research demonstrates transfer learning's versatility across various applications, from number classification to space object detection (Khotsyanovsky, 2022) and remote-sensing scene classification. Studies show that models pre-trained on larger, generic natural image datasets often outperform those trained directly on smaller, specialized datasets, achieving high accuracy rates up to 97% (Emmanuel & Onuodu, 2022).

In CNN-based image classification, model learning is one of the fundamental step in automating classifications based on feature extractions. The overall learning experience of a model mainly depends on the dataset itself. If left unattended, the model may learn “bias” and “variance” within its parameters. In such a case, a tradeoff is needed to happen. The bias-variance tradeoff is a fundamental concept in machine learning describing how model complexity affects two types of error: bias (underfitting) and variance (overfitting). First, underfitting occurs when a model is too simplistic to capture the underlying patterns in the data, leading to poor predictive performance on both training and test dataset, often characterized by high bias and resulting in inaccurate predictions. On the other hand, overfitting refers to a modeling error in machine learning where a model learns the details and noise in the training data to the extent that it negatively impacts its performance on new data because it "learns" too much and familiarizes itself with the dataset severely. Hence, to manage the tradeoff for a disease-detection CNN, techniques like regularization, data augmentation, early stopping, and cross-validation are often used to restrain variance without inflating bias.

Conceptual Framework

Figure 1. Research Paradigm



In this study, Figure 1 serves as the foundation for the study, collectively structuring the compounding theories built from various sets of knowledge and ensuring a structured flow of the paradigm. Firstly, the input stage consists of three major requirements: (1) Knowledge requirements, (2) Hardware requirements and lastly (3) Software requirements. Knowledge requirements include familiarity with plant pathology, computer vision, and machine learning concepts, which guide the design and implementation of the research. Moreover, Hardware inputs such as a camera module, illumination sources, a processing device, and computing devices are essential for capturing and processing such data for classification. Meanwhile, software requirements, including Python libraries, machine learning frameworks, and visualization tools, provide the computational backbone for data analysis and interpretation. These form the input section, which in turn allows the process flow to establish a groundwork for systematic data acquisition and processing.

The process stage outlines the methodological steps that transform inputs into usable outcomes. Data acquisition begins with capturing RGB images of anthracnose disease on mango leaves and collecting a plant dataset, which forms the raw dataset. These readings undergo preprocessing, including calibration, normalization, and noise reduction techniques, to ensure data quality and consistency. Additionally, the study will use a specific convolutional neural network framework, namely MobileNetV2, as the main model for disease classification, and shall be used for transfer learning, and fine-tuning of the model. The refined data then progresses to model development and training, where machine learning algorithms are employed to classify samples and detect patterns. Finally, validation and evaluation procedures are implemented, using performance metrics and cross-validation methods to ensure model reliability and generalizability.

Lastly, the output stage culminates in the development of a predictive model for plant disease detection, which can identify and classify severity conditions based on symptomatic visuals of the leaves. This model not only contributes to disease detection but also enhances agricultural productivity by reducing crop losses and informing timely interventions. Importantly, the IPO model also incorporates a feedback loop, allowing insights from the evaluation stage to inform adjustments in preprocessing, feature selection, or model training.

Statement of the Problem

Anthracnose detection, while critical for the Philippine mango industry, remains a challenge due to the widespread implementation of effective solutions, as unpredictable post-harvest losses stem from latent infections, ineffective traditional visual inspection methods, and the absence of objective, real-time data to resolve problems in the supply chain.

Hence, the study will aim to establish three things: (1) to determine and examine the current situation of the Philippine mango industry, specifically the economic impact of anthracnose, highlighting the challenge of latent infection that renders traditional visual inspection ineffective and creates information asymmetry within the supply chain, (2) to create a computer vision system for harnessing visual features and monitoring the health status of mango leaves, utilizing an affordable RGB camera, an Edge Computing Unit (SBC with Edge TPU), and a Python-based data acquisition pipeline, and, (3) to determine and evaluate the quality and effectiveness of the system's machine learning models, particularly a Convolutional Neural Network (MobileNetV2), in accurately classifying healthy, early-stage, and advanced-stage anthracnose in mango leaves based on their extracted image features, prioritizing metrics such as Recall (Sensitivity) to minimize false negatives and thereby address the economic uncertainty caused by latent infections in the agricultural value chain.

Guided by the said objectives, it will seek to answer the following questions:

1. What are the current methods and technologies employed for the management and detection of anthracnose in Philippine mangoes?
2. What are the stages in the development of the *Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (Mangifera indica L.) Leaves?*
3. How effective is the *Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (Mangifera indica L.) Leaves* , using the classification performance metrics defined within the ISO/IEC TS 4213:2022 standard, particularly in terms of:
   - 3.1 disease classification accuracy,
   - 3.2 precision,
   - 3.3 recall, and
   - 3.4 f-1 score?
4. What is the level of acceptance of the *Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (Mangifera indica L.) Leaves*, as defined within ISO 25010, particularly in terms of:
   - 4.1 functionality,
   - 4.2 performance efficiency,
   - 4.3 usability,
   - 4.4 reliability, and

4.5 maintainability?

Hypotheses

To address the query regarding the performance and effectiveness of the system, the following hypotheses will be formulated:

$H_0 3$: Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (*Mangifera indica* L.) Leaves will not be effective in detecting anthracnose in mango leaves, particularly in terms of disease classification accuracy, precision, recall, and f-1 score.

$H_1 3$: Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (*Mangifera indica* L.) Leaves will be effective in detecting anthracnose in mango leaves, particularly in terms of disease classification accuracy, precision, recall, and f-1 score.

$H_0 4$: There will be no significant difference in the respondent's evaluation of the level of acceptance of the Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (*Mangifera indica* L.) Leaves in relation to the ISO/IEC 25010 standard, particularly in terms of functionality, efficiency, usability, reliability, and maintainability.

$H_1 4$: There will be a significant difference in the respondents' evaluation of the level of acceptance of the Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (*Mangifera indica* L.) Leaves in relation to the ISO/IEC 25010 standard, particularly in terms of functionality, efficiency, usability, reliability, and maintainability.

Scope and Limitations of the Study

This study will focus on developing a computer vision system for the detection of anthracnose in Philippine mangoes. Image data will be harvested using an affordable standard RGB camera sensor integrated with a field-deployable, high-performance Single-Board Computer (SBC), such as the Raspberry Pi. The data will be used to train and deploy a Convolutional Neural Network (CNN) model, specifically inferring a lightweight architecture like MobileNetV2, to classify mango leaves into Healthy, Early-Stage, or Advanced-Stage infection.

The study will be limited to validating the utility and field performance of this specific, affordable, fixed-band RGB sensor and edge computing hardware. It will not delve into the discovery of new optimal spectral peaks or utilize advanced chemometric analyses. Furthermore, the study will be limited by the subjectivity of the visual ground-truthing protocol used for data labeling and its reliance strictly on the visible spectrum. Measurement inconsistency will also be a limitation, as field data collection will remain susceptible to environmental variability, despite the inclusion of portable lighting and imaging setup materials aimed at maintaining data quality.

This study will be conducted from April 2025 to June 2026. The researchers chose Arayat, Pampanga as the venue to conduct research. The respondents of the study will also be mango farmers and landowners from the said locale, and a selected group of experts to evaluate its effectiveness and system quality.

Significance of the Study

The significance of this study lies in its potential to advance accessible smart-agriculture technologies for the Philippine mango industry. Its development is expected to benefit the following sectors:

For Mango Farmers and Landowners. The proposed system will support farmers, particularly those in Arayat, Pampanga, by providing a practical and cost-effective method for early detection of anthracnose in mango leaves. Identifying infections at the leaf stage helps prevent disease spread throughout the canopy, reduces the need for heavy chemical treatments, and protects fruit development, which leads to healthier trees and higher-quality harvests.

For the Department of Agriculture. This research will provide the Department of Agriculture with a practical tool for field-level leaf disease monitoring. A low-cost and scalable detection system can be integrated into DA extension programs to improve orchard health assessments, enhance disease management training, and strengthen sustainable production practices. This contributes to improved quality standards and the global competitiveness of the mango industry.

For Future Researchers. This study provides a strong technical foundation for future work in agricultural imaging. The identified models, dataset, and methodology for mango leaf analysis can guide researchers in developing more advanced and portable detection systems and in applying similar methods to other crop diseases and plant conditions.

Definition of Terms

The researchers conceptually and operationally defined each terminology.

Anthracnose. A fungal disease in mangoes caused by *Colletotrichum gloeosporioides* that produces dark lesions and fruit rot. The focus in this study is its symptomatic stage.

Computer Vision System. A computer vision-based system that is designed to detect symptomatic anthracnose in mangoes in real time, integrating CNN models such as MobileNetV2 and SSD MobileNet) with pixel-based image processing.

Convolutional Neural Network (CNN). A type of deep learning architecture designed to automatically learn and extract spatial features from images. In this study, CNNs are used to analyze RGB images of mangoes to detect anthracnose symptoms and assess severity levels.

Dataset. A collection of annotated mango image data used for training and testing deep learning models. Each image is labeled according to health status or disease severity to enable supervised learning.

Deep Learning Model. A class of machine learning models that use multi-layered neural networks to automatically extract hierarchical features from raw data. In this study, deep learning models such as CNNs are used to classify mango images as healthy or anthracnose-infected and to estimate severity.

Disease Classification Accuracy. An evaluation metric that measures the percentage of mango samples (healthy or infected) correctly identified by the system.

False Positives. These are errors where healthy mangoes are incorrectly classified as diseased.

False Negatives. These are errors where diseased mangoes are incorrectly classified as healthy.

F-1 Score. An evaluation metric, the harmonic mean of precision and recall, is used to measure overall model performance.

Latent Infection. A stage of anthracnose where the disease is present, but the symptoms are not yet visible.

Machine Learning Model. An algorithm that learns from data to make predictions or classifications. In this study, machine learning models are applied to classify mangoes as healthy or anthracnose-infected and to estimate disease severity using image data.

Precision. An evaluation metric, the proportion of mangoes correctly identified as infected out of all those classified as infected.

Recall (Sensitivity). An evaluation metric is the ability of the system to correctly identify mangoes that are truly infected.

Support Vector Machine (SVM). A machine learning algorithm that classifies samples by finding the optimal separating boundary.

Symptomatic Detection. A method of identifying mangoes infected with anthracnose based on visible disease symptoms, such as lesions and discoloration, through image analysis.

True Positives. These are correct classifications where diseased mangoes are accurately classified as diseased.

True Negatives. These are correct classifications where healthy mangoes are accurately classified as healthy.

Chapter 2

REVIEW OF LITERATURE AND STUDIES

This chapter presents the different related literature and studies that are gathered by the researchers for an extensive understanding and review of the variables that will be used in this study. Moreover, included in this section is the synthesis to supply a framework for research questions and hypotheses, and displays the present state of knowledge on the variables under this study.

Challenges in Detecting Mango Anthracnose: Limitations of Current Methods

Anthracnose, caused by the fungus *Colletotrichum gloeosporioides*, is a major postharvest problem and is considered the most serious fungal disease of mangoes in the Philippines (Department of Agriculture - Bureau of Agricultural Research, 2022). Research has identified multiple *Colletotrichum* species associated with mango anthracnose, with *C. gloeosporioides* being the most dominant, followed by *C. asianum*, *C. acutatum*, and *C. siamense* (Rattanakreetakul et al., 2023). The disease creates irregular brown spots and "shotholes" on leaves especially younger ones causing tough spots and blackening the tips, blackens and withers flowers, and produces brown to black sunken spots on the fruit, which can lead to reduced tree vigor and total crop failure (Department of Agriculture - Bureau of Agricultural Research, 2022; Asmita et al., 2022).

To combat these losses, different postharvest control methods have been applied individually or in synergy, classified as chemical, physical, and biological as reviewed by Moreno-Hernández et al. (2024). Chemical methods have traditionally used fungicides, but their improper application has led to the emergence of resistant strains of the pathogen, and their use poses serious risks to human health and the environment due to chemical residues on fruits and their pollutant effects on soil, water, and non-target organisms (Ciofini et al., 2022; Rattanakreetakul et al., 2023). For example, the use of thiophanate-methyl has been associated with severe toxic effects, and prochloraz, while effective, has been listed as a priority pollutant by the US Environmental Protection Agency (EPA) because of its carcinogenic effects (Ciofini et al., 2022). As a result, some governments have introduced regulations on the use of these products, leading to some fungicide being banned. As an alternative, the use of 1-methylcyclopropane (1-MCP), which acts as a ripening suppressant by blocking ethylene receptors, has been explored, and while one study reported it failed to control anthracnose symptoms, another found it inhibited the germination and growth of *C. gloeosporioides* by accumulating Reactive Oxygen Species (ROS). Nitric oxide (NO) has also been shown to reduce anthracnose by 30% and induce the synthesis of defense enzymes like phenylalanine ammonia-lyase (PAL), chitinase (CHI), and polyphenol oxidase (PPO) (Moreno-Hernández et al., 2024).

Physical methods include cold storage, hot water treatment (HWT), and ultraviolet (UV) radiation (Moreno-Hernández et al., 2024). Cold storage is used for fruit preservation, with an optimum temperature for mangoes between 10° and 12.5°C, and storing them at 15°C has been shown to completely inhibit *C. gloeosporioides*; however, some varieties are sensitive to it and can show symptoms of chilling injury. HWT involves dipping newly harvested fruits in water at 52° to 55°C for ten minutes. While HWT is an effective physical method that can reduce anthracnose incidence by 48-57% and is a postharvest requirement for exporting mangoes to the United States, it is not widely practiced by farmers due to the high cost of the equipment, the duration of the treatment, and the lack of a real price advantage in the local market (Department of Agriculture - Bureau of Agricultural Research, 2022). Furthermore, HWT applied after cold storage can cause the fruit to rupture, destroying its market value and cancelling its commercial potential in such a scenario (Javed et al., 2022). UV radiation is used as a postharvest disinfectant and can stimulate the fruit's defense mechanism by inducing the synthesis of enzymes and bioactive compounds, which decreases the attack of *C. gloeosporioides* (Moreno-Hernández et al., 2024).

Biological methods use living organisms or their derivatives to control pathogens. Antagonists such as yeasts (*Meyerozyma caribbica, Torulaspora indica*) and bacteria (*B. subtilis, P. fluorescens*) have been applied to control anthracnose incidence, with reported control rates above 40%. These biological agents compete for nutrients and space and can synthesize antifungal compounds. They are not considered hazardous to human health or the environment; however, their effectiveness can be affected by abiotic factors. Extracts and essential oils are secondary metabolites from plants with antifungal activity. Thymol essential oil, for instance, has been shown to completely control the development of *C. gloeosporioides*, and other effective essential oils include cinnamon, clove, and kaffir lime (Moreno-Hernández et al., 2024). However, a study by Gañán-Betancur et al. (2024) indicated that products based on thyme or tea tree oil are inefficient at controlling anthracnose in the field.

Despite the existence of various Research and Development-developed technologies, there is a very low adoption rate among farmers, which results in persistently high postharvest losses (Department of Agriculture - Bureau of Agricultural Research, 2022). These challenges with traditional and alternative methods underscore the critical need for disease management strategies that are innovative, effective, and sustainable.

Technological Solutions for Anthracnose Detection: Advancements in Computer Vision and Machine Learning

To address the limitations of traditional methods, researchers have been exploring the use of advanced technologies, particularly machine learning (ML) and deep learning (DL), for the automatic and non-destructive detection of mango diseases. These methods offer significant advantages, such as being less time-consuming and requiring fewer resources compared to manual inspection (Joshi et al., 2024; Faye et al., 2022).

A significant advancement in this area is the development of computer vision systems (CVS) for early disease detection. One particularly effective approach involves the use of Ultraviolet A (UV-A) illumination combined with color information analysis. UV-A light enhances disease-related color information that is invisible to the naked eye, enabling the detection of anthracnose at least one day earlier than conventional visual inspection (Ramírez Alberto et al., 2022; Reyes et al., 2024). The UV-Linear Discriminant Analysis (UV-LDA) method, for instance, achieved an accuracy of 0.97 and a precision of 0.95 for the early semantic segmentation of healthy and diseased mango fruit areas (Ramírez Alberto et al., 2022).

Researchers have proposed various ML and DL-based solutions for the automatic diagnosis of mango diseases. These methods have shown impressive results by learning complex features directly from raw images, which reduces the need for extensive pre-processing (Faye et al., 2022; Sharma et al., 2023). A hybrid model combining a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM) has been proposed for mango fruit disease detection, yielding a high detection accuracy of 99% (Kumar et al., 2025). Other CNN-based models have also demonstrated high accuracy, with one study achieving 90-95% on a testing set for identifying mango leaf disease (Patel et al., 2025), and another attaining a test accuracy of 90.36% (Sharma et al., 2023). A Modified Dense Convolutional Network (MDCN) model utilizing transfer learning achieved an accuracy of over 99% (Chandrashekar et al., 2024), while the "You Only Look Once, Version 3" (YOLOv3) system, a CNN-based model, achieved an accuracy of 83.33% in detecting anthracnose in mango leaves (Yumang et al., 2023).

The superior feature extraction and autonomous learning capabilities of CNNs make them the cornerstone of modern computer vision in agriculture (Dhanya et al., 2022; Zhao et al., 2024). Further advancements in mango leaf disease detection leverage sophisticated CNN architectures. For instance, a study employing an ensemble of deep learning architectures, including DenseNet121, EfficientNetB2, MobileNetV2, ResNet50, VGG16, and VGG19, found that ResNet50 exhibited unparalleled accuracy at 99.12% for mango leaf disease identification (Bairwa et al., 2024). Furthermore, CNN and SVM models have been successfully used to properly diagnose the degree of anthracnose illness in mango leaf samples, demonstrating an outstanding accuracy of 97% across various severity classifications (Mir et al., 2024). Hybrid deep learning models have also shown exceptional performance, with a combination of ResNet50V2 and EfficientNetB1 achieving a perfect 100% accuracy on a test set for classifying multiple mango leaf diseases, including anthracnose (Shweta Bhattacharjee Porna et al., 2024). The use of pre-trained models like ResNet-50 has also been validated, where its features, fed into machine learning classifiers like SVM and Logistic Regression, achieved a 100% accuracy in the binary classification of healthy and diseased mango leaves (Sandhya S et al., 2022). The successful application of CNNs for mango fruit detection and classification using architectures like Resnet-18 for quality assessment further underscores their potential for agricultural quality control (Peón et al., 2025).

Despite the potential of these technologies, challenges remain. The models proposed so far often suffer from a lack of training data, and most current models do not provide real-time diagnosis. The presence of multiple diseases and variations in real-world conditions also make feature extraction and disease identification a difficult task (Faye et al., 2022).

However, computer vision and deep learning, particularly with the use of CNNs which are the cornerstone of modern approaches, are creating high-quality, non-contact, and efficient solutions across various agricultural activities, including plant health monitoring (Dhanya et al., 2022; Zhao et al., 2024; Peón et al., 2025). The integration of CNN-based models in CVS provides a strong foundation for accurate and early disease detection, supporting targeted intervention in precision agriculture (Ramírez Alberto et al., 2022; Reyes et al., 2024).

Evaluation Metrics for Computer Vision and Machine Learning Systems in Mango Anthracnose Detection

Real-time computer vision systems have emerged as effective solutions for monitoring crop diseases due to their ability to provide non-destructive, rapid, and scalable detection. In mango production, researchers have applied lightweight deep learning models to accurately detect anthracnose with high accuracy under practical conditions. In the study conducted by Nithya et al. (2022), convolutional neural networks (CNNs) have demonstrated a reliable classification of healthy and diseased mango fruits, achieving over 98% accuracy in defect detection. Zooming out beyond simple classification, Faye et al. (2025) introduced a deep learning framework capable of both disease identification and severity estimation through pixel-level lesion analysis, successfully categorizing anthracnose into multiple severity stages. These advancements highlight the feasibility of developing lightweight CNNs such as MobileNetV2 and SSD MobileNet in real-time systems, where detection and severity grading are achieved through the combination of object recognition and pixel-based image processing. This technological approach facilitates timely disease intervention while also supporting quality assurance and reducing postharvest losses, underscoring its importance for sustaining mango production in the Philippines.

Classification accuracy refers to the proportion of correctly identified samples relative to the total, providing an overall measure of how well a model distinguishes between healthy and diseased fruits or leaves. In the context of mango detection, computer vision–based systems using RGB imaging and CNNs have demonstrated outstanding results. For instance, Nithya et al. (2022) developed a CNN-based defect detection system for mango fruits, achieving 98.5% accuracy in distinguishing healthy from defective samples. Similarly, Pathak et al. (2024) developed a CNN-based system for detecting multiple mango leaf diseases, achieving ~99% accuracy across eight classes, including anthracnose. In a related study, Faye et al. (2025) integrated image segmentation with deep learning to classify the severity of mango fruit diseases, including anthracnose, achieving 97.82% accuracy. These studies highlight the capacity of CNN-based computer vision systems to reliably and accurately detect anthracnose symptoms, supporting their integration into real-time field and postharvest applications.

Precision measures the proportion of positive disease predictions that are truly diseased, making it particularly critical in symptomatic anthracnose detection in Philippine mangoes. High precision ensures that healthy mangoes are not mistakenly classified as diseased, preventing unnecessary rejection of marketable fruit and minimizing economic losses. Studies have shown effectiveness, such as hybrid models: a Convolutional Neural Network (CNN)-Random Forest approach attained precision rates between 91.12% and 97.83% when classifying anthracnose severity in mango leaves (Bhatia et al., 2024). On the other hand, CNN-SVM models for mango anthracnose reported precision consistently above 90% across severity levels, showing low false positive rates (Mir et al., 2024). Additionally, hybrid CNN-SVM systems achieved precision values exceeding 97% for mango scab, validating the reliability of these techniques in practical fruit disease management (Kaur et al., 2024). These findings show that computer vision systems can deliver highly accurate positive predictions, enabling reliable detection of anthracnose and supporting informed decision-making for Philippine mango growers.

Recall, or sensitivity, measures the proportion of actual diseased samples correctly identified by the model. In detecting anthracnose in Philippine mangoes, high recall ensures that infected fruits are not overlooked, preventing diseased produce from entering the supply chain. In comparable studies, in terms of mango disease detection, they highlight this capability: a CNN-Random Forest hybrid report recall values of 91.32% to 99.27% for classifying anthracnose severity in mango leaves (Bhatia et al., 2024), while similar CNN-Random Forest models attained 95.43% to 98.28% recall across severity levels in mango powdered leaf disease (Banerjee et al., 2023). Moreover, other models, like the hybrid CNN-SVM model, achieved 96.28% recall for mango scab, showing reliability in reducing false negatives (Kaur et al., 2024). These findings indicate that computer vision–based systems can reliably capture diseased samples, minimize false negatives, and support timely interventions in Philippine mango production.

F-1 score is a significant metric for measuring the performance of machine learning systems for disease detection in agriculture because it provides a harmonic mean of precision and recall, giving equal weights to false positives and false negatives. For symptomatic anthracnose detection in the Philippines, a high F-1 score indicates the system can accurately identify diseased samples while minimizing misclassifications, which is essential for effective disease management and reducing postharvest losses. Various studies utilizing hybrid deep learning frameworks integrated with CNN and Random Forest or SVM have attained F-1 scores between 92.63% and 98.16%, indicating robust effectiveness in both precision and recall across various severity levels of mango leaf diseases (Bhatia et al., 2024; Banerjee et al., 2023; Mir et al., 2024). For example, Bhatia et al. (2024) found that the CNN + RF model achieved F-1 scores ranging from 92.63% to 96.64% for assessing anthracnose severity in mango leaves, while Banerjee et al. (2023) reported F-1 scores between 95.06% and 98.16% in the evaluation of powdered leaf disease, emphasizing the model's ability to accurately determine both mild and severe infections. Furthermore, Mir et al. (2024) showed that CNN and SVM models reliably achieved F-1 scores near 92%, maintaining balance between precise predictions and comprehensive coverage of affected samples. These findings collectively underscore that the F-1 score is an effective measure for evaluating computer vision–based systems, reflecting their ability to provide reliable and timely detection of symptomatic anthracnose in mangoes.

Functional Suitability and the Underlying Skepticism in Agricultural Technologies

In the context of ISO/IEC 25010 (n.d.), functional suitability refers to the degree to which a product or system provides functions that meet stated and implied needs when used under specified conditions. For an agricultural diagnostic tool, such as the proposed system, this translates to providing accurate, reliable, and trustworthy information that can be used to make better decisions. However, the said standard reveals that functionality is not an objective static property of the hardware alone, but a perception from a combination of the device's technical performance, user's pre-existing knowledge, and the clarity of transforming data into action.

As such, a challenge to the perceived functionality of any agricultural diagnostic tool is the trust it needs to gain from users, mainly farmers. Traditional farming practices are rooted in knowledge from experience, honed by years of direct, manual observation. Hence, a new technology must prove its value against these established, trusted means. (McGrath et al., 2024) notes, successful development requires bringing together the scientific knowledge of technology and researchers, with the “experiential knowledge” of farmers.

Several studies reveal skepticism amongst farmers towards new technologies, often stemming from previous experiences of utilizing innovations that failed to fulfill their promises (Shoaib, 2025). Kenny and Regan (n.d.) found that “technology trust issues” were a significant deterrent to farmers’ engagement with smartphone technology and agricultural apps. This creates a dynamic where objective data from a sensor may be questioned or rejected if it contradicts a farmer’s experiential assessment. As Gardezi and Stock (n.d.) found, trust is a central concern that creates skepticism about the value of digital technologies. This is not an irrational rejection, but is rooted in weighing between a new, unproven source against a lifetime of proven experience.

Furthermore, the core value of the proposed system is the use of low-cost hardware for accessibility. However, this comes with an inherent trade-off between affordable, portable sensors and expensive, laboratory-grade instruments. Hence, functional suitability also concerns whether the equipment is viable enough for the intended task. A sensor that is 94.2% accurate in the field, as demonstrated in Piedad et al. (n.d.), and is widely adopted to prevent crop loss, may have a far greater impact than a 99.99% accurate laboratory instrument but remains inaccessible due to cost and complexity. As the study's primary goal is to help farmers in making better, more timely decisions using the detection system, the functional benchmark is not absolute accuracy but rather its fitness for a specific purpose, provided that the data collected is reliable enough for decisions that produce desirable outcomes.

Finally, actionability and data presentation also concerns functional suitability. Sensors being accurate and fully trusted are irrelevant if the results cannot be presented in a way that leads to a clear and confident decision. Nebiker et al. (n.d.) highlight a significant gap, wherein farmers can become overwhelmed by data overload if the information is not presented in a clear, actionable way. While ways to bridge this gap, such as Decision Support Systems (DSS), are helpful, its problem lies in the lack of proper explanation on how it works (Bellon-Maurel et al., 2022). Thus, it becomes a dilemma on whether to prioritize actionability or trust and usability. As Cartolano et al. (2024) note, the lack of explainable AI frameworks in smart agriculture leads to trust issues among farmers, agronomists, and policy makers, making them hesitant to adopt AI-based recommendations if they cannot verify the logic behind the algorithmic outputs.

Efficiency and the Return of Investment and Effort in Precision Agriculture

According to ISO/IEC 25010 (n.d.), performance efficiency concerns resources expended in relation to the results achieved. In an agricultural context, this translates to the farmer's calculation of their return on investment that constitutes a holistic assessment of economic benefits against a wide range of costs, including time, labor, and cognitive effort. The literature demonstrates that for a technology to be perceived as efficient, its value must be clear, compelling, and account for the full scope of resources a farmer must expend to adopt and integrate it.

The most frequently mentioned barrier for the adoption of precision agriculture technologies is economic, as expected. High investment costs are a primary deterrent, particularly for smallholder farmers who operate on a thin profit margin and have limited access to capital. Even for technologies marketed as “low-cost”, the initial outlay can be prohibitive. Shoaib (2025) found that 56% of emerging-market farmers cited high upfront costs as the primary reason for not adopting new technologies. This financial barrier is also compounded by an often unclear or unproven return of investment. Farmers are risk-averse, and without a clear indication of profitability, they are hesitant to invest in unproven tools. The hesitation for technological adoption is not solely because of the technology itself but rather complicated further by factors such as insecure land ownership, limited access to credit and financing, which all deter long-term investments (Shoaib, 2025).

Beyond economic merits and challenges, users perceive efficiency through resource optimization. A key value of precision agriculture, such as the proposed system, is its ability to enable more targeted application of inputs, and studies provide strong evidence that users recognize and value this benefit. The Environmental Benefits of Precision Agriculture Quantified (n.d.) report that the adoption of various precision technologies leads to significant efficiency gains, including a 7% increase in fertilizer placement efficiency, a 9% reduction in herbicide and pesticide use, a 6% reduction in fossil fuel use, and a 4% reduction in water use.

These resource gains translate directly into tangible benefits. For example, soil moisture sensors have been shown to cut water usage by 20-30% by preventing wasteful overwatering (Tektelic, 2025). Furthermore, another study by Muharomah et al. (2025) regarding a smart greenhouse system demonstrated a 20% reduction in water usage and an impressive 103% return on investment (ROI). These quantifiable improvements in input efficiency are a convincing factor for adoption, as they provide clear and understandable merit.

Additionally, studies reveal the role of perceived environmental co-benefits as a component of overall efficiency. While immediate economic returns are a priority for most farmers, there is a growing recognition of the long-term value of sustainable practices. The ability of sensor technologies to reduce fertilizer and chemical leaching, conserve water, and improve long-term soil health is seen as a valuable advantage that contributes to more sustainable and resilient agricultural systems (Government Accountability Office, 2024).

While economic and resource analysis is indeed important, using it solely to determine a technology's efficiency is incomplete because it ignores the significant, non-monetary investments that a farmer must make. A simple ROI calculation might compare the hardware cost to the expected savings on inputs. However, the literature consistently shows that farmers view lack of time, lack of qualified labor, and insufficient training as major barriers to adoption (AgriMarketing.com - Barriers to Adoption of Digital Agriculture in Nebraska, n.d.). These are not merely inconveniences; they are costs. The time a farmer spends learning to use a complex new software interface is time that cannot be spent on other critical farm tasks, representing a direct opportunity cost (Barriers and Considerations for Ag-tech Adoption, 2024).

Usability, Participatory Design, and Farmer-Centric Approaches in an Agricultural Context

Usability, as defined by ISO/IEC 25010 (n.d.), refers to the degree to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use. It is arguably the most critical factor for technologies deployed in the field. A failure to account for the reality that the agricultural context is unique, demanding, and has a user base that is diverse in its technical proficiency through a rigorous, user-centered design process is a primary cause of failure in technology adoption.

The different physical environment of a farm imposes several constraints on designing user interfaces. First, users are often outdoors, exposed to bright sunlight, dust, moisture, and vibrations, and may be operating machinery or wearing gloves (Sebald et al., 2024). These conditions make standard interface design conventions obsolete and ineffective. Hence, user feedback from usability tests of agricultural hardware and software provides a clear set of design principles. Farmers consistently prioritize intuitive operation and menu navigation, as complex or nested menus are difficult to use while performing other tasks (Sebald et al., 2024). There is a strong preference for large, clear control panels and buttons that are easily accessible. Additionally, many users preferred text labels over abstract icons, which at first may seem more ambiguous, and report frustration with unreliable touch functions on screens that may be dirty or wet. Thus, there is a stated preference for haptic, physical buttons for the most frequently used functions, as they provide tactile feedback and more reliable in harsh conditions (Sebald et al., 2024).

For mobile-connected devices, effective data visualization is paramount, as it translates complex sensor data into effective, noticeable insights. Simple, clear charts, graphs, and interactive maps are far more effective than raw, numerical readouts, allowing farmers to quickly assess crop health or soil conditions and make timely decisions (Qaltivate, 2024). A critical usability requirement for these mobile applications is the ability to function effectively in areas with no limited or no internet connectivity. Designing applications that are functional offline or in low-bandwidth situations can ensure wider accessibility (Qaltivate, 2024).

However, a challenge for usability remains to be the diverse demographic with a wide spectrum of age, education, and technological proficiency. A sophisticated, featured-pack set might be useful in a young, tech-savvy farmer, but it can be completely useless and inaccessible for an older farmer with limited experience with digital technology. Therefore, a design philosophy in agricultural technology prioritizes simplicity, clarity, and a minimal learning curve (Qaltivate, 2024). The philosophy should center around creating systems that are ready to use immediately and require little to no formal training. A scoping review by Osman et al. (2022) found that the most widely applied user interface elements for smallholder agriculture are audio and Interactive Voice Response (IVR), which allows users to interact with applications in their local language or dialect, making technology accessible to semi-literate farmers. Designing for the least proficient user often results in a more intuitive and usable product for everyone.

The standard methodology of researchers developing a solution in a lab, completely cutting off beneficiaries, and then pushing it to them later, has often resulted in tools that are poorly aligned with the practical realities of agriculture and has led to low adoption rates. The problem lies in developers who, as they are working outside the agricultural context, often overlook the unique needs and constraints of farmers, leading to a fundamental mismatch between technology and its intended use. Thus, the most effective way to ensure a technology is usable is not to design it for farmers, but to design it with farmers (Aditya et al., 2025). A user-centered, participatory design process is a foundational methodology that determines the technology's success in wide adoption and application (Yunianto & Wahyudi, 2025). This approach involves engaging farmers as active partners throughout the entire development life cycle, from initial identification of a problem and co-creation of potential solutions to the iterative testing and refinement of prototypes. By involving users, developers gain invaluable insights into the criteria that farmers themselves use to evaluate a technology's performance and usability, which often differ from the metrics prioritized by researchers. This inherent alignment with the user dramatically increases the technology's perceived usability and compatibility, which becomes a primary driver for acceptance and use.

Reliability, Maintainability, and The Importance of Long-Term Viability in Agricultural Technology

While usability revolves around ease of interaction with the technology, reliability and maintainability speak to its long-term viability and the user's ability to depend on it over a long period of time. In a field where equipment failure during the critical planting or harvest window can have severe financial consequences, these characteristics are important. ISO/IEC 25010 standard (n.d.) defines reliability in terms of maturity, availability, and fault tolerance, while maintainability includes analyzability, modifiability, and testability.

Agricultural environments are harsh and fundamentally hostile to sensitive electronic equipment. Technologies deployed in the field are subjected to constant bombardment of environmental stressors such as extreme temperatures, high humidity, direct sun exposure, rain, dust, chemical sprays, shock, and vibration. A device’s ability to withstand these conditions are primary component of its perceived reliability. The use of appropriately rated enclosures is a critical first line of defense. Standards like NEMA 4X and Ingress Protection (IP) ratings such as IP65, IP66, and IP67 specify a component’s resistance to dust and water intrusion, with higher ratings indicating protection against powerful water jets or even temporary submersion (Born, 2025). The choice of materials is equally important: UV-resistant polycarbonates are often favored for their ability to withstand unpredictable weather conditions, including heat, UV rays, rain, sleet, hail, and snow without deteriorating. Additionally, specialized, ruggedized connectors designed for harsh environments are essential for maintaining secure electrical connections despite moisture and vibration (Fibox USA, n.d.). Beyond enclosure and materials, the long-term reliability of the sensors themselves is a major concern, as they are prone to frequent faults due to poor deployment environments and remote deployment locations (Born, 2025). These can manifest as complete hardware failure, also known as “hard faults”, or more insidious “soft faults” (Miller et al., 2025). Sensor drift, bias, and a general decline in accuracy are common issues that can corrupt the data stream and undermine the user’s trust in the entire system, leading to incorrect and costly management decisions.

A system’s reliability is inherently linked to the effort required in maintaining it. From the perspective of the user, a high maintenance burden detracts from the technology’s value and can be a barrier for adoption. One of the most critical maintenance tasks for any sensor-based system is the need for periodic recalibration. As sensors age or are exposed to environmental stressors mentioned before, their readings can drift, necessitating recalibration to ensure data accuracy, which can be complex and time-consuming (Verma, 2025).

When hardware does fail or software glitches occur, the availability of technical support is vital. Smallholders cannot often diagnose and repair equipment themselves and can face costly delays and crop losses while waiting for technical support (Precision Agriculture, n.d.). A lack of local experts and easy-access troubleshooting help is a frequently cited barrier, contributing to the perception that a technology is unreliable because it is unmaintained (Miller et al., 2025).

Furthermore, power management is a fundamental challenge for the long-term, reliable deployment of remote sensors. The limited lifespan of batteries necessitates a regular and labor-intensive maintenance schedule for replacement, which is often impractical and costly for devices deployed across larger or remote areas. This problem has resulted in research into alternative solutions, such as wireless power transfer and energy harvesting technologies, which aim to create self-powered sensors that can operate sustainably for long periods, thereby drastically reducing the maintenance burden and improving overall system reliability (Huda et al., 2022).

Finally, network connectivity in these precision agricultural devices is not an external dependency; it is an integral component of the system's own reliability. While an expert might view the sensor hardware, the cloud platform, and the rural internet infrastructure as separate systems, the user does not make this distinction. The user's goal is to receive timely actionable information, and if it fails to arrive because of poor mobile or internet service, they view it as the failure of the product itself rather than the network infrastructure it depends on (Nebiker et al., n.d.).

Hence, the well-documented reality of poor connectivity and infrastructure in rural areas is not to be ignored or offloaded to telecommunication providers. This problem is a constraint that must be addressed in designing the technology's architecture. Strategies include incorporating offline functionality, allowing data to be collected and stored on the device when a connection is unavailable and synchronized later (Qaltivate, 2024). Another approach is to move data processing from the distant cloud to the device itself, also known as "edge computing". This allows the device to perform analysis and provide immediate feedback to the user in the field without needing a constant internet connection. The use of alternative communication protocols, such as Low-Power Wide-Area Networks (LPWANs), can also provide more robust and energy-efficient connectivity for sensor networks in remote areas (Miller et al., 2025).

Synthesis of the Reviewed Literature and Studies

The Philippine mango industry, a cornerstone of the natural agricultural economy, is confronted by a persistent challenge: postharvest losses caused by anthracnose that can decimate up to 30.4% production. The reviewed literature establishes that the nature of this fungal disease lies in its latency, where infections remain dormant and invisible during harvest, only to emerge during ripening and transport. This single characteristic of the disease makes traditional management strategies inadequate, as visual inspection is rendered obsolete. Furthermore, chemical, physical, and biological controls, despite their respective advantages, are limited by pathogen resistance, costs, low adoption rates, and inconsistent field effectiveness.

In response to this problem, several studies have explored a variety of technologies as a solution. Particularly, among these technologies is the use of machine learning, deep learning and computer vision systems for early disease detection. Significant advancement in the said areas, such as the use of UV-A illumination, color information analysis, and the use of modern deep-learning models such as Convolutional Neural Network (CNN) have resulted in high detection accuracy, often exceeding 90 to 95 percent. However, literatures surrounding these technologies have revealed a significant gap. This includes lack of training data, lack of real-time diagnosis, difficulty in feature extraction and disease identification.

While computer vision and deep learning presents a viable path moving forward, the literature that technical efficacy alone is insufficient for it to be successful. A truly effective solution must be validated and addressed both reliability and user-centric adoptability. In developing the system, it must consist of rigorous technical performance benchmarks, such as accuracy, precision and F-1 score. Furthermore, the literature highlights the importance of recall (sensitivity) to minimize the impact of false negatives, where a single undetected diseased fruit can compromise an entire shipment.

Additionally, a holistic, user-centric evaluation, in adherence with ISO/IEC 25010 standard, which addresses the human factors that come with adopting technology, must also be considered in developing the system. The reviewed literature details a series of challenges concerning this dilemma: the trust deficit, where new sensor data must compete with farmer's experiential knowledge; the total cost of adoption, which extends beyond initial price and also includes a farmer's time, training, and cognitive effort; the unique demands of usability in harsh agricultural environments for a user base with a wide digital literacy divide; and the need for long-term reliability and maintainability, including physical robustness and the ability to function in areas with poor connectivity.

The body of reviewed literature presents a clear and compelling insight: the success of an agricultural technology is determined by its alignment with the user's holistic reality. The understanding that a solution must be validated against both quantitative performance metrics and qualitative criteria through a participatory process provides the justification for the methodology of the proposed system. The proposed study is therefore positioned as a direct response to the gaps identified, aiming to develop a solution that is not only technically effective but also genuinely viable, valuable, and trustworthy for the farmers of the Philippine mango industry.

Chapter 3

METHODOLOGY

This chapter presents the research design, description of the research instruments used, statistical treatment to be used, as well as the process flow chart and the design project flow.

Research Design

The researchers will utilize descriptive, experimental, and developmental research designs to achieve the study's objectives.

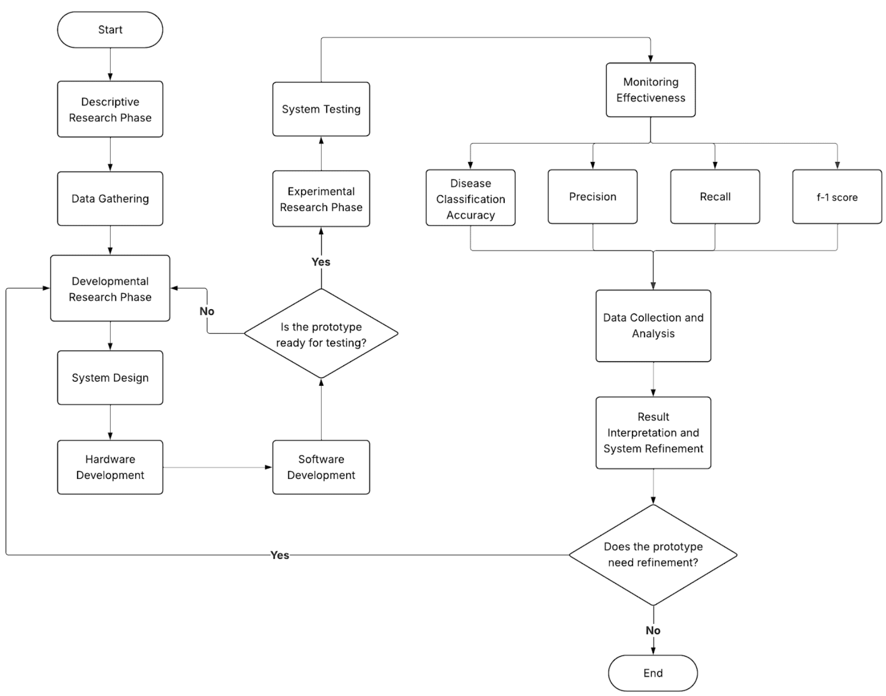
The descriptive method will be used to establish the context of the problem, detailing the economic and cultural significance of the Philippine mango and the devastating impact of anthracnose, particularly its latent infection, which creates a significant information asymmetry in the supply chain. It also described the scientific principles of computer vision technology as a tool for plant health assessment, explaining how anthracnose can be detected via visual cues and deep learning.

The experimental method was central to determining if the computer vision system, particularly the camera module, were sufficient to build a functional model for classifying anthracnose. This involved a field data collection protocol that included selecting multiple trees, taking averaged readings per leaf, and aiming for a balanced dataset. A standardized visual ground-truthing protocol was implemented to assign 'Healthy,' 'Early-Stage Infection,' or 'Advanced-Stage Infection' labels, serving as the ground truth for model training. Supervised deep learning models, particularly Convolutional Neural Network (CNN), were trained and evaluated, with Recall (Sensitivity) prioritized as the most critical performance metric to minimize false negatives in the supply chain.

The developmental method was used in designing, developing, and evaluating the system proposed. This included the selection and assembly of affordable, off-the-shelf hardware components, specifically the camera module and a Raspberry Pi microcomputer. Software development involved creating the deep-learning model for detection and classification, as well as developing a supplementary mobile application for user access. The evaluation also considered the system's inherent limitations and proposed avenues for future development, such as hardware enhancements and expansion for differential diagnosis.

Flowchart of Research Design/Process Flowchart

Figure 2. Project Process Flowchart



The research design of the study will follow a structured process combining descriptive, developmental, and experimental methods. The process will begin with the Descriptive Research Phase, in which the researchers will gather data on existing systems and methods for disease detection in agricultural crops, with emphasis on anthracnose in Philippine mangoes. This process will include the identification of current practices in monitoring, early detection, and classification of mango diseases, as well as related computer vision techniques and machine learning approaches for image-based plant disease detection. After gathering data, it will then proceed to the developmental research phase, which will involve the design of the system architecture. In the process of this phase, the researchers will conceptualize the hardware and software design components of the real-time computer vision system for anthracnose detection and severity estimation.

After finalizing the system architecture, the development of hardware components will begin. This will include the construction of a prototype equipped with an RGB camera and an embedded computing device capable of capturing real-time images of mango leaves. Proper lighting setup and calibration techniques will be applied to ensure consistent and accurate image quality. Next, software development will take place, which includes programming routines for image acquisition, preprocessing pipelines (such as noise reduction, segmentation, and image enhancement), and the implementation of machine learning algorithms. After the development of the hardware and software of the system, it will then proceed to an evaluation for the system's preparedness. If the prototype fails the evaluation for testing, it will undergo additional refinement and development; otherwise, it will proceed to the Experimental Research Phase.

In the experimental phase, system testing will be conducted to determine the accuracy and reliability of the disease detection and classification features. Disease classification accuracy, precision, recall, and f-1 score will be monitored by the system. Data will be collected during the testing, and it will be analyzed to determine the effectiveness and accuracy of the system. After the collection and analysis, it will be followed by Result Interpretation and System Refinement, in which the performance will be assessed based on ISO 25010 quality attributes such as functionality, efficiency, usability, reliability, and maintainability. If the results show an indication of the need for refinement, the system will be re-evaluated and improved accordingly; otherwise, the development will be considered complete.

Description of Research Instrument Used

A researcher-made questionnaire was drafted to acquire data from the respondents. The questions were related to the study's objectives and research questions. The questionnaire consists of closed-ended questions designed to gather data regarding the respondents' knowledge, perception and experience.

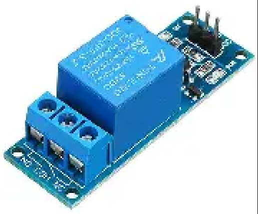
Material Requirements

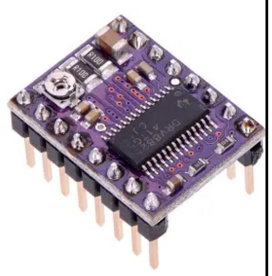
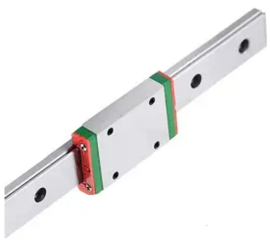
This section discusses the materials required for developing both the hardware and software components of the system. Table 1 presents a summarized checklist of these materials, including their specifications and relevant information.

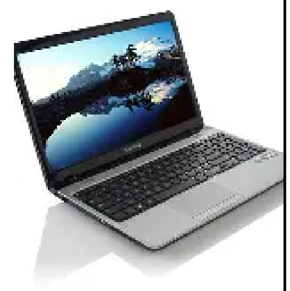
Table 1

Material Requirements

Component	Image	Description	Application
Raspberry Pi Camera Module 3 (12 MP)		A Raspberry pi camera that has 75 degrees diagonal FOV with a focus of 10 cm	Captures mango leaf images
LED array		12V 10W LED strips	Provides lights
Light Diffuser		Provides consistent, controlled light source for measurements	Provides controlled and repeatable lighting so measurements are consistent.
Raspberry Pi 4 4GB		Handles data acquisition, preprocessing, UI, and storage	Processes captured spectral data and manages device control functions.

3.7V Li-ion rechargeable batteries		Provides portable operation for field use	Supplies portable energy to operate the device for several hours in the field.
microSD card		Saves spectral data, logs, and small images	Stores all collected spectra, images, and logs for later
3D-printed Enclosure		Protects components and ensures ergonomic handheld use	Protects components while allowing ergonomic handheld use in real environments.
IR Led Proximity Sensor		Allows user to gather information about the distance between the sensor and object	Allows the system to stop upon reaching the maximum threshold of camera displacement
Single Module 5V Relay		Allows the switching integration of circuits	Allows the 12V power supply to safely flow to the LED strips

LM2596		An adjustable DC-DC buck converter that inputs a large voltage and outputs a stable adjustable voltage	Allows the system to step down its 16.8V power supply to a stable 12V 3A
Stepper Motor		a brushless DC electric motor that rotates in a series of small and discrete angular steps.	Allows the displacement of camera to ensure frame-by-frame picture
Stepper motor Driver (DRV8825)		A driver for stepper motor	Allows to safely drive the stepper motor
Gear Rack and Pinion		a mechanical system that consists of a linear rack and a rotational pinion gear	Allows the displacement of camera to ensure frame-by-frame picture
CNC Slider		Is a linear bearing designed to provide free motion in one direction	Allows the displacement of camera to ensure frame-by-frame picture

Computing Device		Allows heavy computation for machine learning	Used for training data for machine learning

Statistical Treatment

The data that will be gathered in this study will be treated statistically using the following statistical tools:

1. Frequencies and Percentage

This statistical tool will be used to analyze the current technologies used in detecting mango anthracnose in the Philippines. The responses of the five (5) agricultural specialists will be organized according to the types of technologies they identify. Frequency will refer to the number of experts who identify each specific technology in their responses, and the percentage will be calculated using the formula:

$$\% = \frac{f}{N} \times 100$$

Where,

$\%$ = Percentage

f = Frequency

N = Total number of respondents

This method will allow the researchers to identify which technologies are commonly used and recognized by professionals in the industry, providing a descriptive overview of the current state of mango anthracnose detection in the country.

2. Classification Model Performance Evaluation

These statistical tools will be used to evaluate the performance of the Convolutional Neural Network (CNN) architectures employed for the detection and severity estimation of anthracnose in mango leaves.

Table 2

3-Class Confusion Matrix for Anthracnose Detection

Predicted

		Healthy	Early	Advanced
Actual	Healthy	True Negative	False Negative	False Negative
	Early	False Positive	True Positive	Misclassified
	Advanced	False Positive	Misclassified	True Positive

This matrix will serve as a visual and quantitative summary of the model's performance, highlighting where it succeeds and where it makes mistakes. Specifically, it will show the number of correct classifications, True Positives (TP) and True Negatives (TN), for each class and misclassifications, False Positives (FP) and False Negatives (FN), revealing which type of errors the model is making.

After populating the confusion matrix, the performance metrics will be calculated from its values using the following formulas:

Table 3

Performance Metrics and their Formulas

Performance	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F-1 score	$2 \times \frac{Precision \times Recall}{Precision+Recall}$

Where,

Accuracy = general measure of the overall correctness, showing the percentage of all predictions that were correct

Precision = assesses the model's reliability when it predicts a positive class (e.g., Early or Advanced)

Recall = measures the model's ability to find all actual positive cases

F-1 score = a single, balanced metric that combines both precision and recall

3. Weighted Mean

The Weighted Mean will be used to find out the system's level of acceptability based on ISO25010 system's quality standards. The following formula will be used:

$$WM = \frac{\sum wf}{f}$$

Where,

WM = Weighted Mean

$\sum wf$ = Summation of weighted frequency

f = Frequency

A five-point Likert scale will be used to evaluate the system's quality. Respondents will rate their level of agreement with each item using the following verbal descriptions and corresponding interpretations.

Table 4

Five-Point Likert Scale

Score	Range	Verbal Description	Meaning
5	4.21 – 5.00	Very High Acceptance	The respondent is fully satisfied, suggesting that the system performs exceptionally well in meeting the specified quality attribute.
4	3.41 – 4.20	High Acceptance	The respondent is mostly satisfied, suggesting that the system meets the quality attribute effectively, though some minor improvements may be needed.
3	2.61 – 3.40	Moderate Acceptance	The respondent is neutral or somewhat satisfied, indicating that the system meets the quality attribute to some extent but still has noticeable areas for improvement.

2	1.81 – 2.60	Low Acceptance	The respondent is dissatisfied, suggesting that the system falls short in meeting the quality attribute in many aspects.
1	1.00 – 1.80	Very Low Acceptance	The respondent is completely dissatisfied, indicating that the system does not meet the quality attribute at all.

This statistical method will be utilized to assess the system's acceptability, grounded in the user's perspective, by evaluating its performance across the five quality attributes defined by the ISO 25010 standard: functionality, performance efficiency, usability, reliability, and maintainability.

4. Combined Mean

The Composite or Combined Mean will be used to determine the overall acceptance level of the system by calculating the average of the weighted means from all five ISO25010 attributes. The following formula will be used to provide a single numerical value that reflects the respondents' collective evaluation of the system:

$$CM = \frac{n_1\bar{x}_1 + n_2\bar{x}_2}{n_1 + n_2}$$

Where,

CM = Combined Mean

n_1 = Number of items in the first group

n_2 = Number of items in the second group

$\bar{x}_1$ = Mean of the first group

$\bar{x}_2$ = Mean of the second group

5. McNemar's Test

This statistical test will be used to determine whether there is a significant difference between the performance of the machine learning model and human experts in classifying mango leaf diseases. McNemar's test is appropriate for paired categorical data, where both the human and the model classify the same samples.

The 2×2 contingency table will be constructed as follows:

Experts	Model Correct	Model Incorrect
Human Correct	a	b
Human Incorrect	c	d

The test focuses on the discordant pairs (b and c) to determine if the difference in classification accuracy between human and model is statistically significant. The formula for McNemar's test is:

$$x^2 = \frac{(|b-c|-1)^2}{b+c}$$

Where:

x^2 = McNemar's test statistic

b = Number of samples correctly classified by the expert but not by the model

c = Number of samples correctly classified by the model but not by the expert

The computed χ^2 value will be compared with the critical value at $\alpha = 0.05$. If the p-value is less than 0.05, the null hypothesis will be rejected, indicating a significant difference in their classification performance.

Because the classification involves three categories (Healthy, Early, Advanced), a Stuart–Maxwell test (generalized McNemar) will also be used to determine whether there are significant differences in the overall distribution of classifications between the model and the human experts.

6. Mann–Whitney U Test

This statistical treatment will be used to determine whether there is a significant difference in the respondents' evaluation of the system's level of acceptance between the two independent groups of participants.

The Mann–Whitney U test is a non-parametric alternative to the independent-samples t-test, appropriate for ordinal data such as the 5-point Likert-scale ratings used for the ISO 25010 quality attributes (functionality, performance efficiency, usability, reliability, and maintainability).

It does not assume normal distribution of scores and is therefore suitable for small-sample or skewed data.

The formula for the Mann–Whitney U test is:

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1$$

Where:

U	=	Mann–Whitney test statistic
n_1	=	Number of respondents in Group 1
n_2	=	Number of respondents in Group 2

R_1 = Sum of the ranks for Group 1

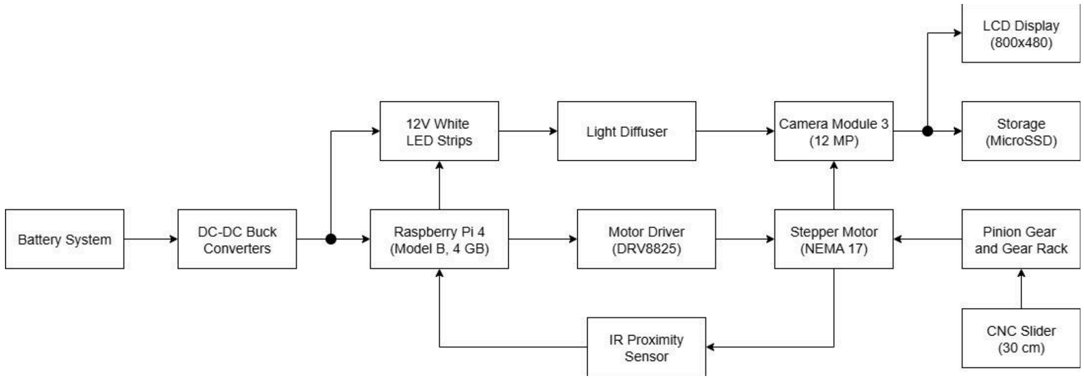
After ranking all observations from both groups combined, the smaller of the two U values is used to determine significance.

The computed U statistic will be converted to a *z*-value and compared with the critical value at α = 0.05.

If the p-value is less than 0.05, the null hypothesis will be rejected, indicating a significant difference in the acceptance ratings between the two groups.

Design Project Flow

Figure 3.1 Hardware Flow Diagram of the Design Project



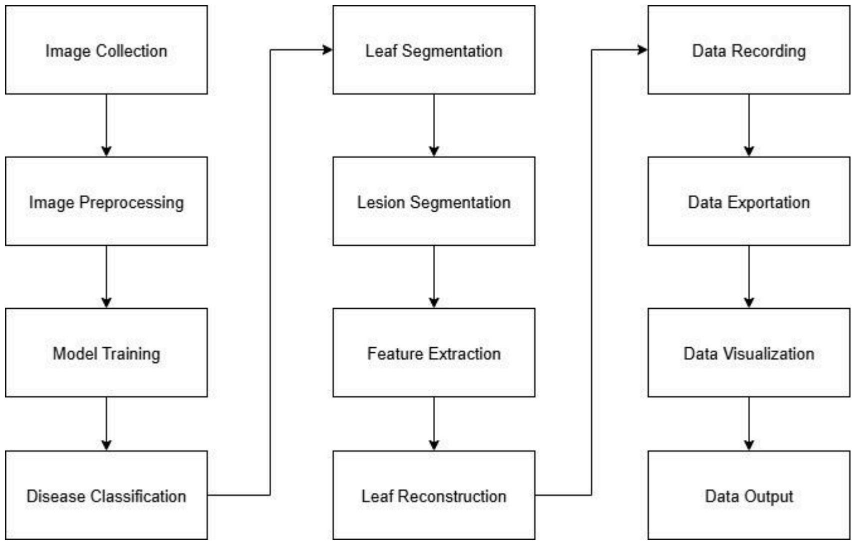
The design project flow will be divided into two main parts: Hardware Flow Diagram (Figure 3.1) and Software Flow Diagram (Figure 3.2). In the hardware structure flow, the diagram will actively discuss the shared relationship and interconnection between hardware components utilized in the study. This will include all electronics and mechanical materials that are present throughout the prototyping stage, outlining the physical architecture of the study. Meanwhile, the

Software Structure Flow discusses the linear processes that govern the system's operation, starting from Image collection to feature extraction and image integration.

Detailing the hardware flow diagram, the project flow begins with the battery system, providing stable voltage and management of power distribution throughout the electronics. This will be paired with DC-DC buck converters for an appropriate voltage rating and safe current flow. The main line will be subdivided into two parts: The automation of the stepper motor through the feedback signal of the IR sensor and Raspberry Pi 4, and the LED lighting system. The Pi is directly connected to both the camera module and LCD, wired with a 15-pin connector through their corresponding DSI/CSI ports. Meanwhile, the GPIO pins of the Raspberry Pi are connected through the driver of the motor, which in turn is connected to the stepper motor. The IR sensor will serve as the feedback to allow the stepper motor to go to a certain distance limit, and will send a signal to the Raspberry Pi 4. This will be synchronous with the LED lighting system, allowing an optimized usage of power for long-lasting use.

The mechanical apparatus, consisting of a 26-teeth Pinion Gear and Gear Rack assembly, allows the rotation of the stepper motor to translate its rotational motion into linear movement. To seamlessly move the motor, it is adapted to the CNC slider, allowing a guide that moves linearly in one direction. While the stepper motor is actively powered on, the LED system is also opened in parallel, allowing a clear image collection of mango leaf images. This will be implemented with a light diffuser to avoid focusing the light on one place and overlighting the camera while scanning. After such process, the LCD display will output the scanned leaf along with its biological description, while the saved image will be saved locally. This flow illustrates a cohesive electro-mechanical loop where power, control, sensing, and actuation are intricately linked.

Figure 3.2 Software Flow Diagram of the Design Project



After the acquisition of images using hardware components, the Raspberry Pi 4 will process the data from the acquired mango leaf image using computer vision and deep learning frameworks. The process begins with binding snapshots of mango into full images using phase correlation and image segmentation. Then it will be passed to Image Preprocessing for standardization, wherein resizing, color space conversion, and noise filtering through morphological operations are applied to enhance the image quality and consistency. This defines the standards of leaf images, ensuring that shadows or background clutter will not interfere with the processes.

After identifying the leaf, Lesion Segmentation will be conducted. In this stage, the system will detect diseased areas using HSV thresholds and morphological cleaning to highlight the infected regions accurately. Quantitative features are also extracted from the segmented regions, calculating leaf area, shape, color, and severity through pixel-to-cm conversion. The severity is then calculated by taking the ratio between the sum of lesion areas and total leaf area,and is represented by a percentage value. Other metrics include average color values and geometric descriptors such as convex hull and ellipse fit are also computed. By analyzing these features, the system can predict and report the extent of the infected area and nature of infection, allowing a more precise classification of severity.

If a leaf is severely damaged and may consist of multiple missing sections, a leaf reconstruction will be applied for estimation of leaf shape prediction. To attain this, geometric reconstruction techniques such as convex hull or ellipse fitting are applied. More specifically, convex hull connects outermost points to approximate its full original shape, while ellipse fitting is used for estimating ideal leaf boundaries. Such computation are implemented through the use of OpenCV, and is accounted for usage of computer vision.

Lastly, the recorded data is stored in a database for external use. The data collected will undergo data cleaning and data processing, similar to the processes of mango leaf images. This will then be utilized for output on both the LCD display and Mobile Application, each both have their own software system.

Field Experiment

The field experiment is designed as a multi-stage process that integrates descriptive, developmental, and experimental research designs to evaluate the proposed system's real-world performance and viability. The experiment will be conducted at a designated orchard in Arayat, Pampanga, involving researchers, local mango farmers, and a selected group of agricultural specialists. The experiment is divided into two: a technical validation to assess the machine learning model's diagnostic accuracy and a user-centric evaluation to determine the system's practical acceptability according to ISO/IEC 25010 standards.

The initial phases involve preparation and sample collection, where researchers will select multiple mango trees to ensure a diverse sample set. On these trees, individual leaves will be classified into three categories: Healthy, Early-Stage Infection, and Advance Stage Infection. To establish a reliable baseline for machine learning model training, a standardized visual ground-truthing protocol will be done, wherein each selected leaf will be independently classified by at least two experts to create a consensus-based label, which will serve as the ground truth.

Following the selection of samples, the next phase will involve data acquisition using the system prototype. To mitigate measurement inconsistency in field conditions, a fixed sensor distance and angle will be followed, and multiple readings will be averaged from each leaf to create a single, representative spectral signature under consistent ambient lighting. This process will generate a complete, labelled dataset for the machine learning phase.

Once the dataset is complied with, it will undergo preprocessing, including normalization and noise reduction, to ensure data quality. Next, the dataset will be divided with the biggest part used to train the machine learning models: a Decision Tree and a Support Vector Machine (SVM) model. Technical validation will be done by evaluating the trained models on the unseen testing set. Quantitative measurements of performance will be done through a 3-class confusion matrix and a suite of key metrics, namely accuracy, precision, F-1 score, and recall. The recall metric will be mainly focused on as it is the most important in the case of minimizing false negatives, which therefore represent the highest economic risk in the mango supply chain caused by latent infections.

The user-centric evaluation will, however, run alongside the technical one and is aimed at assessing the system's practical value. A hands-on session with the prototype system will be arranged for a group of mango farmers to take part in. Based on their interaction, they will fill out a questionnaire made by a researcher to evaluate the system against five quality attributes of ISO/IEC 25010 standard: functionality, efficiency, usability, reliability, and maintainability. The five-point Likert scale will be used for collecting the responses which will then be processed with the help of a weighted mean to get the level of acceptance for each attribute and an overall score of user acceptance for the system. By the combination of technical and user-focused phases, the field experiment is a comprehensive and realistic assessment of the system's potential, its diagnostic accuracy balanced with its ease of use and value in the hands of Filipino farmers.

Multiple Constraints

In the development of Field-Based Computer Vision System for Anthracnose Detection and Severity Estimation in Mango (Mangifera indica L.) Leaves, multiple constraints and challenges should be considered to ensure the system's effectiveness and reliability.

Subjectivity of Visual Ground-Truthing. The project's reliance on a standardized visual classification protocol for labeling leaf health is a practical adaptation, but it introduces inherent subjectivity and potential label noise into the training data. This method is less objective and reliable than laboratory-based techniques like Polymerase Chain Reaction (PCR) analysis, which can impact model performance.

Measurement Inconsistency in Field Conditions. Field-based spectral measurements are susceptible to environmental variability and operator inconsistency. Factors such as changes in ambient lighting, inconsistent sensor-to-leaf distance, and variations in the angle of measurement can introduce noise and non-repeatability into the collected dataset, potentially impacting the robustness of the machine learning model.

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