BANANACHECK: A MOBILE-BASED CONVOLUTIONAL NEURAL NETWORK FOR BANANA DISEASE DETECTION AND ADVISORY

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CHAPTER I

INTRODUCTION

The Problem and its Setting

Bananas are one of the most consumed and cultivated fruits across the world, serving as a nutritional food for its richness in potassium, and a livelihood most especially in the tropical and subtropical regions. According to the Food and Agriculture Organization (2022), bananas are one of the key factors in economic development and food security, most notably in Latin America (LATAM), Africa and Southeast Asia (SEA) valued at over $10 billion annualy. Despite this, bananas are susceptible to many diseases, many of which affect the leaves, leading to lower yield and financial degradation for farmers. Black Sigatoka, Bacterial Wilt and Panama Disease pose as a threat to the worldwide production of bananas.

Here in the Philippines, it serves as a major component an important agricultural export of rural economies. It is consistently among the country's top fruit crops, with over 9 million metric tons produced in 2022 alone (Philippine Statistics Authority, 2023). Banana ranks among the top fruits produced in the country, with the likes of Northern Mindanao, SOCCSKSARGEN, and Davao leading in production volume. Nonetheless, banana farms, both commercial and backyard based, have been greatly affected by disease outbreaks. These are aggrevated by a lack of timely disease detection tools, its high cost, and access to expert agricultural support once the symptoms become severe.

Locally, banana farmers and barangay agricultural workers often lack the tools, infrastructure, and training to diagnose these diseases early. Most of them solely rely on visual inspection, which can lead to innacurate or delayed responses. This can result in loss of crops, which affect the food supply and their income. Areas with poor internet connectivity limit access online for diagnosis tools, making the real time support much worse and difficult.

To address this, this study proposes the development of Artificial Intelligence (AI) Banana Lead Analyzer using a mobile device. The system allows users to take a photo of the banana leaf, even offline, and receive a diagnosis of the leaf's conditiion. By using AI, this empowers farmers and agricultural staff with a fast, accessible, and cost-effective method of detecting diseases, helping reduce crop loss, strengthen the industry, and improve treatment response time. According to Mustofa et al. (2023), they highlighted the effectiveness of CNN-based architectures in plant leaf disease detection across different crops, and shows that despite the small dataset, it can still produce results with proper training.

Literature Review

Convolutional Neural Network (CNN) serves as a standard for image analysis, especially for plant disease detection. This is due to their hierarchal feature extraction capabilities in which CNN, and custom architectures are used 93% of the time for published plant disease models (AgriAI Benchmark Report, 2023).

Arulmozhi et al. (2023) specifically affressed banana leaf diseases, achieving 94% accuracy in distinguishing Sigatoka, Panama, and healthy leaves, despite variations in orientation and lighting using ResNet50 model on field images from Indian plantations. They emphasized the significance of dataset diversity, recommending partnerships with agricultural agencies. A study by Singh et al. (2023) justifies our partnership with the agricultural office to collect field grade images, ensuring our model's validity as they found biases in AI models trained mainly on lab curated plant images. They found differences in background clutter and lighting.

A study by Mohanty et al. (2022) emphasized ResNet's performance in achieving over 90% accuracy despite having an imbalanced and small dataset. They underscored transfer learning as a critical strategy real world agricultural application, where sometimes labeled data is scarce.

Conceptual Framework

This study is anchored in the Input-Process-Output (IPO) model shown in Figure 1, which provides a structured approach for developing the AI-based banana leaf disease detection system intended to assist the City Agriculturist Office (CAO) of the Local Government Unit (LGU). This model serves as a roadmap that outlines how the necessary components of the project are organized and transformed from basic resources into a functional, intelligent system that addresses the needs of both the public and the CAO staff.

In the Input phase, the app relies on three key inputs to function effectively. First, farmers capture images of banana leaves using their smartphone cameras, providing real-world visual data of both healthy and diseased specimens. These photos reflect actual field conditions, including variations in lighting, angles, and growth stages, ensuring the AI learns from authentic examples rather than controlled lab environments. Second, farmers contribute valuable observations about disease progression and environmental factors, such as weather patterns preceding symptom appearance. This traditional knowledge helps contextualize the visual data. Third, agricultural experts validate a subset of images by labeling them with accurate disease identifications and severity ratings, creating a verified training dataset that accounts for regional disease variants specific to Mindanao.

The Process phase transforms raw inputs into actionable insights through three core processes. Initially, captured images undergo standardization through automated cropping to isolate leaves, resolution adjustment to 224x224 pixels, and color normalization for consistency. The system then employs a lightweight ResNet50 neural network to analyze visual patterns in the processed images, identifying disease markers like lesion shapes and discoloration patterns. This model has been specifically fine-tuned on local banana varieties and common regional diseases. Finally, the AI's predictions are cross-referenced with an agricultural knowledge base to filter improbable results and generate practical recommendations. The system prioritizes recall over precision to minimize missed detections of critical diseases, while still providing confidence estimates to help farmers gauge result reliability.

The Output phase receive three types of practical outputs from the system. The primary output is a diagnostic report featuring the original leaf image overlaid with visual indicators highlighting affected areas, accompanied by a clear diagnosis in local language (e.g., "Black Sigatoka detected with 90% confidence"). The app provides culturally appropriate treatment recommendations, delivered through multiple formats including concise text instructions in Cebuano or Tagalog, and visual infographics demonstrating proper treatment. Lastly, the system generates aggregated, anonymized disease reports that help agricultural agencies monitor regional outbreaks and allocate resources effectively, while maintaining individual farmer privacy through an opt-in data sharing system.

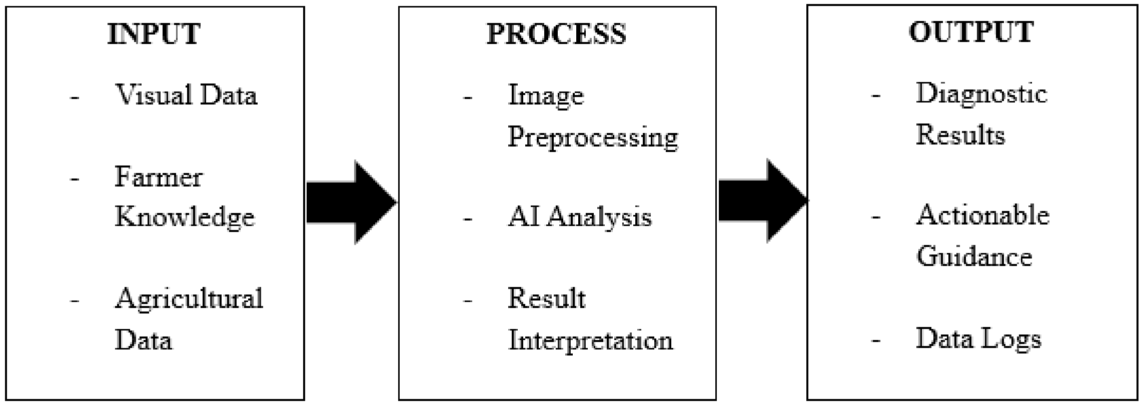

Figure 1. Conceptual Framework

Statement of the Problem

Diseases on banana leaves like Sigatoka, Banana bunchy top virus, and Fusarium wilt, threaten livelihood in the Philippines. According to Philippine Statistics Authority (2023), Bananas rank as the top agricultural export generating P36.1 billion yearly and supporting 1.2 million farmers. Another study from Philippine Fiber Industry Development Authority (PhilFIDA) (2023), shows that despite the economic importance, smallholder farmers face tough challenges in managing diseases, with 60% reporting P150,000 – P300,000 per hectare losses due to late detection. Manual scouting, generic AI apps, and expensive lab tests falter from human error and inaccuracy which fails to aid what local farmers need (IRRI, 2023). This capstone bridges these gaps by developing a valid CNN model trained on banana leaves in the Philippines with partnership with local offices. This aims to deliver an accurate, affordable and farmer friendly solution to empower local farmers with real time diagnostics and to prevent crop losses.

Scope and Delimitation

Scope of the Study

This research focuses on developing an AI-based banana disease detection system using a ResNet50 model for smartphones. The study includes collecting and preprocessing field images of banana leaves from Conel, Batomelong and Katangawan, General Santos City. The AI is integrated into a Flutter based app with offline functionality. The system will be tested for accuracy, and usability for farmers across 3 barangays. Validation will measure both technical performance (precision, recall) and practical metrics (farmer adoption rates, diagnostic match rates with field observations).

Delimitation

This research is limited to four common leaf diseases (Black Sigatoka, Fusarium wilt, Moko Disease, and Banana Bract Mosaic Disease), not including soil-borne pathogens or nutritional shortages that require lab analysis. The geographic range includes only disease strains specific to Mindanao, with data gathered from farms smaller than 5 hectares. The technical execution does not feature real-time video assessment, multispectral imaging, or compatibility with iOS. Although the system offers diagnostic outcomes and treatment recommendations, it does not assess the financial implications of disease management, nor does it consider sociocultural obstacles to technology acceptance among farmers. Testing will happen only on Android devices (version 9+) that represent typical smartphones used by farmers in the target area.

Significance of the Study

This research shows significance for General Santos City's agricultural sector, because it addresses the issue of managing banana diseases. By making an AI based banana leaf disease detector, it provides local farmers with an accessible, and a low-cost diagnostic tool, minimizing the reliance on high-cost lab tests and reducing crop loss caused by delayed disease identification. Using field images from GenSan and nearby Sarangani areas, guarantees a higher accuracy for regional disease strains, unlke generic apps trained on foreign datasets. This study also contributes to sustainable farming practices by enabling early detection, reducing too much use of pesticides. Additionally, it advances AI applications in Phillipine agritech, showing how lightweight deep learning models can be optimized for low resource settings. The findings may also guide policymakers In digitizing agricultural extension services, supporting the Department of Agriculture's "Plant, Plant, Plant" program. Lastly, this empowers local farmers by fostering resilience and food security in SOCSKSARGEN's banana industry.

CHAPTER II

METHODOLOGY

Research Design

The BananaCheck research design focused on the integration of image-based machine learning, expert disease classification, and user feedback to deliver an effective and practical solution for banana disease identification. The core of the system was built around a Convolutional Neural Network (CNN) model trained to recognize common banana leaf diseases, including Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease based on captured leaf images from farms in General Santos City and nearby areas. The system's development was guided by factors such as image quality, data labeling accuracy, disease symptom visibility, and the consistency of environmental conditions (lighting, angles, etc.). According to LeCun et al. (2015), CNNs are effective in agricultural image classification tasks due to their ability to extract and learn complex visual patterns, making them ideal for real-time plant disease diagnosis using leaf imagery.

Initially, an extensive collection of banana leaf images was gathered and annotated by agricultural specialists in collaboration with the Office of Agriculture. This authenticated dataset provided the foundation for training the CNN model. The model's effectiveness was assessed through metrics like accuracy, precision, recall, and F1 score to guarantee dependability across various agricultural environments.

Additionally, the system incorporated a user interface (UI) that enables farmers and technicians to submit leaf images via mobile devices. The interface was created with user-friendliness at its core delivering quick, clear, and understandable results like the recognized illness and recommended actions. According to Zhang (2021), agricultural AI tools that are accessible should focus on simplicity, quickness, and user-friendliness to promote uptake among rural users who possess differing levels of digital skills. This research design prioritized technical dependability, contextual significance, and user-focused feedback to guarantee that the BananaCheck system is both scientifically precise and locally applicable and available for banana growers in the Philippines.

Selection of Respondents

The respondents for this study were composed **of** banana farmers**,** agricultural technicians**,** and farm cooperative managers from General Santos City and surrounding agricultural zones. These individuals were selected due to their direct involvement in banana cultivation and disease management, making them suitable sources of relevant and practical information for evaluating the effectiveness and usability of the Banana Disease Detection System.

Locale of the Study

The research was carried out in General Santos City, an important agricultural region in the southern part of the Philippines. Recognized for its cultivation of numerous high-value crops such as bananas, the city is an excellent site because of the availability of smallholder banana farms and commercial plantations. Multiple barangays and agricultural communities were recognized as key sources of information and participants, especially those engaged in banana farming. In particular, the barangays of Conel, Batomelong, Katanggawan, and Ligaya were chosen because of their active participation in banana farming and their persistent struggles with crop diseases. This site was selected not just for its accessibility but also due to the common occurrence of banana diseases, which still impact crop production and farmers' earnings. Selecting General Santos City and specifically these barangays aligns with the study's goals, which focus on aiding local farmers by utilizing an AI-based disease detection system that promotes early diagnosis and efficient disease management strategies.

Research Instrument

The research instruments for this banana disease detection system consisted of quantitative methods designed to evaluate usability, accuracy, and user satisfaction in a structured and measurable manner. A survey questionnaire was administered to a representative sample of individuals involved in banana farming and plant disease monitoring. These respondents included banana farmers, agricultural technicians, and cooperative managers from General Santos City and nearby areas. The questionnaire aimed to gather feedback on several aspects of the system, including its ease of use, the clarity of results, and its practical value in field settings. Additionally, the instrument collected data on the respondents' current disease detection methods and their level of experience in banana farming. This provided baseline information for comparing the traditional approaches versus the system's AI-assisted diagnosis.

To ensure structured feedback, the questionnaire utilized a 4-point Likert scale to measure users' levels of agreement with key statements about the system's functionality. The four response options Strongly Disagree, Disagree, Agree, and Strongly Agree were selected to eliminate neutral bias and encourage respondents to take a clear stance. This approach helps provide sharper insights into how users perceive the reliability and usefulness of the system in actual farming conditions. By using this quantitative instrument, the study was able to generate measurable data regarding the effectiveness and user experience of the BananaCheck detection system. The data collected served as the basis for evaluating the system's readiness for real-world applications and for identifying areas for improvement, particularly in usability and image-based diagnosis performance.

Data Gathering procedure

A formal letter of request was submitted to the City Agriculturist Office to seek permission and assistance in identifying suitable sites for conducting the study. After review, an assigned agriculturist recommended four potential locations for future data collection: Barangay Conel, Batomelong, Katangawan, and Ligaya. These areas were selected based on accessibility and the presence of smallholder banana farms affected by common diseases such as Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease. These recommendations will guide the coordination with farm owners and local agricultural personnel for the planned research activities. As part of the upcoming data-gathering process, farm visits will be scheduled to capture images of both healthy and diseased banana leaves. The collected images will then undergo expert validation by a certified plant pathologist and an agricultural technician, who will classify them into four categories Healthy, such as Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease. This process aims to ensure the development of a verified and reliable dataset for training the Convolutional Neural Network (CNN).

Software Process Model

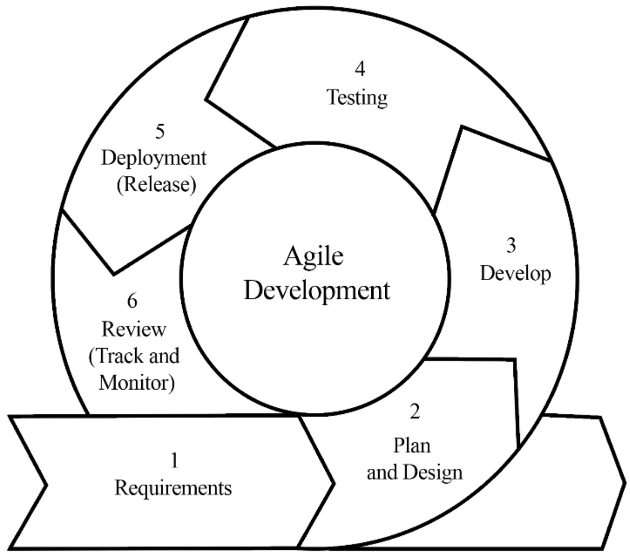

Figure 2. Agile Methodology (Adapted for BananaCheck)

Agile Methodology was adopted for the development of *BananaCheck: A CNN-Based Banana Disease Detection System*. This iterative and user-focused methodology allowed the team to continuously gather feedback, adapt to user needs, and improve system functionality through multiple development cycles. Agile enabled flexibility in integrating expert labeling, real-time image classification, and usability testing within agricultural field settings.

Phase 1. Requirements

The initial phase includes collecting requirements by consulting with stakeholders such as banana farmers, agricultural experts, and representatives from cooperatives. Interviews, field observations, and the analysis of agricultural extension bulletins will be carried out to pinpoint practical difficulties in identifying banana diseases. This stage focuses on identifying specific diseases to address specifically such as Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease and to detail essential system functionalities like image uploading, disease identification, and advisory message creation. This phase will result in a clear list of categories for banana diseases, contributions from stakeholders, and a prioritized collection of system requirements.

Phase 2. Plan and Design

This phase will focus on designing the system's architecture and user interface. Wireframes and flow diagrams will be created to outline the structure and user journey of the application. The planning process will also cover hardware and software requirements, stages of model training, and strategies for future field deployment. Early designs will be refined through feedback loops involving agricultural experts to ensure usability and relevance. Deliverables from this phase will include the system architecture diagram, user interface mockups, and a detailed development plan.

Phase 3. Develop

The development phase will involve building the system through incremental iterations. Key tasks will include training a Convolutional Neural Network (CNN) using annotated banana leaf images, implementing the user interface for uploading images and viewing detection results, and integrating the image classification model with the application's logic. Each development iteration will result in a working prototype that is refined based on performance assessments. Outputs from this phase will consist of a trained CNN model, a functional web or mobile interface, and technical documentation of the codebase.

Phase 4. Testing

After each development cycle, testing will be carried out to evaluate the system's functionality and performance. This will include model testing using a validation set of images to measure accuracy, precision, and recall. Usability testing will also be conducted with selected users to assess the clarity, effectiveness, and ease of use of the interface. Where applicable, field testing will be carried out using actual banana leaf samples. The expected outputs will include performance metrics, user testing reports, and detailed logs of system errors and corresponding fixes.

Phase 5. Deployment (Release)

Following successful validation, the system will be deployed in a controlled field environment. During this phase, the prototype will be used in real-world conditions by banana farmers and agricultural technicians to identify banana leaf diseases. Basic instructional materials, including a user guide and onboarding resources, will be provided to support the initial adoption of the system. Deliverables for this phase will include a field-ready prototype, user support documentation, and initial user feedback regarding performance and usability.

Phase 6. Review (Track and Monitor)

The final phase involves monitoring the system's usage and collecting feedback to evaluate its effectiveness in disease detection. Post-deployment evaluations will be conducted through surveys and interviews to gather insights on usability, accuracy, and relevance in rural farming contexts. A project review will be performed to document lessons learned, identify challenges, and suggest areas for future improvement. Outputs will include user evaluation reports, usage logs, and recommendations for system updates and long-term enhancement.

Data Analysis

In applying statistical tools for the analysis of data, it utilized the following method while analyzing the data gathered from the survey:

Percentage Frequency. This was employed to assess the result obtained from the questionnaires that were distributed to the respondents.

Frequency = (f x w)

Wherein:

f = Number of responses for a particular option

w = Weight (value of the rating: 5, 4, 3, 2, 1)

Mean Formula. To gauge the general perception of both the implemented system and the User Accepance Test, the mean was utilized with Likert Scale.

Weighted Mean = $\bar{X}=\sum w \sum (w \cdot x)$

Wherein:

$\sum(f \times w)$ = summation of all responses

N = Total number of respondents

Range	Program Design	Content and Features	Usability	Acceptability
4.21 – 5.00	Very Acceptable	Very Acceptable	Very Acceptable	Very Acceptable
3.41 – 4.20	Acceptable	Acceptable	Acceptable	Acceptable
2.61 – 3.40	Fairly Acceptable	Fairly Acceptable	Fairly Acceptable	Fairly Acceptable
1.81 – 2.60	Unacceptable	Unacceptable	Unacceptable	Unacceptable
1.00 – 1.80	Very Unnaceptable	Very Unnaceptable	Very Unnaceptable	Very Unnaceptable

Where:

Excellent, Very Usable, Very Reliable (4.21 – 5.00) – The Banana Disease Detector System as a whole is functioning excellently in terms of functionality, suitability, usability, and reliability.

Very Good, Usable, Reliable (3.41 – 4.20) – The Banana Disease Detector System as a whole is functioning well, but the features are moderately good in terms of the functionality, suitability, usability, and reliability.

Good Fairly Usable, Fairly Reliable (2.61 – 3.41) – The Banana Disease Detector System as a whole is functioning well, but the features are moderately good in terms of the functionality, suitability, usability, and reliability.

Fair, Unusable, Unreliable (1.81 – 2.60) – The Banana Disease Detector System as a whole is functioning unfairly in terms of the functionality, suitability, usability, and reliability.

Poor, Very Unusable, Very Unreliable (1.00 – 1.80) – The Banana Disease Detection System as a whole is functioning poorly, and the features are limited in terms of the functionaliy, suitability, usabiltiy, and reliability.

Sentiment Score

The Sentiment Score is a number that is derived by getting the average of each question listed on the Likert Scale. A passing score falls within the 2.61 – 3.40 range, indicating a good, fairly usable, and fairly reliable sentiment. Meanwile, the highest passing score ranges from 4.21 – 5.00, signifying an interpretation of excellent, very usable, and very reliable.

Ethical Considerations

Informed Consent. Before participants interact with the system, they were provided with clear information about the purpose of the study and the nature of their participation. Informed consent was obtained from all users, ensuring they understood how their data will be used and their right to withdraw from the study at any time without consequence.

Confidentiality and Privacy. User interactions with the system are stored securely, and any personally identifiable information (PII) is anonymised to protect user privacy. Data encryption and secure storage practices are employed to safeguard sensitive information. Access to data is restricted to authorized personnel only, ensyrubg compliance with relevant data protection regulations, such as GDPR or local data privacy laws.

Data Use. The data collected from user interactions were used exclusively for research purposes. Aggregated and anonymised data were analyzed to assess the performance of the system and to improve its functionality. Individual user data are not disclosed or used for any purpose other than those specified in the research.

Feedback and Improvement. Users were encouraged to provide feedback on their experience with the system. This feedback was used to make iterative improvements to the system. Users are informed that their feedback was be used to enhance the system's performance and were assured that their input will be handled respectfully and confidentially.

Conflict of Interest. The research team declared that there are no conflicts of interest that could influence the study's outcomes or the interpretation of the data.

CHAPTER III

RESULTS & DISCUSSION

System Overview

The banana disease detection system utilizes a ResNet-50 model optimized for mobile development. According to Chen et al (2023), ResNet-50 achieved 87.6% accuracy on banana leaf disease detection, outperforming MobileNet for small lesion identification. Designed specifically for the local GenSan farmers, this Flutter-based application can process images while maintaining offline functionality. The solution bridges AI diagnostics with practical farming needs by providing instant, explainable disease assessments coupled with localized treatment recommendations

System Objectives

The proposed BananaCheck system is designed to serve as an intelligent, offline-capable diagnostic tool to assist banana farmers and agricultural workers in detecting and managing common banana leaf diseases. By integrating deep learning, mobile development, and field-based data collection, the system aims to empower smallholder farmers with accessible and accurate plant health assessments. The following are the system's core objectives, explained in greater detail:

1. **Detect Banana Leaf Diseases Through AI-Based Image Analysis**

   The system allows users to capture banana leaf images using a smartphone camera. These images are processed using a convolutional neural network (CNN), specifically a lightweight ResNet50 model, to detect signs of three major banana leaf diseases: Black Sigatoka, Fusarium Wilt, Moko Disease, and Banana Bract Mosaic Disease. By relying on visual data rather than manual inspection, this objective helps reduce diagnostic delays, minimize human error, and provide timely alerts to farmers in the field.

2. **Enable Full Offline Functionality for Remote Farming Communities**

   Recognizing that many rural areas lack stable internet access, the system is built to function without requiring a live internet connection. Once installed, users can perform disease detection and receive treatment advice entirely offline. This objective ensures inclusivity and accessibility for farmers in geographically isolated barangays with limited connectivity.

3. **Train and Validate the AI Model Using Real-World Field Images**

   The CNN model is trained using field-grade images collected from banana farms in General Santos City. This real-world dataset improves the model's accuracy in natural conditions, including variations in lighting, background, and leaf damage severity

4. **Train and Validate the AI Model Using Field-Grade Images**

   To ensure high accuracy and contextual relevance, the CNN model is trained on actual leaf images collected from banana farms in Conel, Batomelong, and Katangawan, General Santos City. These field-grade images capture natural variations in lighting, orientation, and leaf condition, providing the model with real-world complexity often missing in lab-based datasets.

System Scope & Limitations

Scope

The proposed system focuses on the development of a mobile-based application that enables banana farmers to detect common leaf diseases using artificial intelligence (AI). Its core functionality is to process images of banana leaves taken through a smartphone camera and provide accurate diagnoses and treatment recommendations even without internet access. The system is built using a convolutional neural network (ResNet50), integrated into a Flutter-based Android application designed for use in rural agricultural settings.

Key components within the system's scope include:

1. A user-friendly mobile interface that allows farmers to capture and upload banana leaf images.
2. An integrated AI module that uses a ResNet50 model to detect and classify three diseases: Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease.
3. Offline functionality that enables full disease detection and diagnosis without the need for internet connectivity.
4. Localized advisory content, including treatment recommendations in Cebuano or Tagalog, supplemented with visual guides.

The scope is focused on Android-based mobile devices and supports farmers and agricultural workers in selected barangays within General Santos City. The system is intended for diagnostic and advisory use and does not include commercial or financial tools.

Limitation

While the system provides valuable support for disease identification and early intervention, several limitations are acknowledged in its implementation:

1. No Support for iOS or Web Platforms: The system is developed exclusively for Android (version 9+) and does not support iOS devices or web browsers.
2. Dependence on Image Quality: The accuracy of detection depends on the clarity and quality of the leaf image captured. Poor lighting, motion blur, or incomplete images may result in incorrect or inconclusive diagnoses.
3. Disease Coverage Restriction: The AI model is limited to identifying only three leaf diseases and does not detect root, stem, soil-based diseases, or nutrient deficiencies.
4. Exclusion of Real-Time Video or Multispectral Analysis: The system relies on still images and does not include advanced imaging features such as video scanning or multispectral sensors.
5. Non-Economic in Scope: The system does not assess the financial impact of the diseases or calculate potential crop losses. It also excludes tools for cost-benefit analysis of treatments.

System Functions

The BananaCheck App is designed with several core functional components to support real-time banana disease detection and provide actionable guidance to farmers in remote agricultural areas. Below is a detailed breakdown of each key function:

Capturing and Submitting Banana Leaf Images via Camera or Gallery

The application allows users to capture real-time images of banana leaves using their smartphone's camera or select existing photos from the device gallery. The camera interface includes a built-in grid overlay to help users properly center the leaf for optimal image quality. Once a photo is taken or selected, users are presented with options to either proceed with analysis or retake the image to ensure clarity and accuracy.

Processing the Image Using a Trained CNN Model (ResNet50)

After image capture, the app runs a locally embedded Convolutional Neural Network (CNN), specifically the ResNet50 model, to analyze the visual features of the banana leaf. The model is trained to identify patterns associated with three common diseases: as Fusarium Wilt, Black Sigatoka, Moko Disease, and Banana Bract Mosaic Disease. The system performs this analysis offline, allowing full functionality even in areas with limited or no internet connectivity.

Generating Disease Diagnosis with Confidence Score

Once the analysis is complete, the system generates a diagnostic result that includes the identified disease, a confidence percentage (e.g., "Fusarium Wilt – 92% Confidence"), and overlays visual markers indicating affected leaf areas. This function enables farmers to make informed decisions based on AI-backed predictions, especially in cases where early intervention is crucial.

Displaying Treatment Recommendations in Local Language

Based on the identified disease, the app displays clear and concise treatment guidelines written in local languages such as Tagalog. These recommendations are complemented by visual infographics to ensure understanding even for users with low literacy or limited farming experience. This function ensures that disease diagnosis is followed by actionable and practical advice.

Maintaining Data Privacy and Offline Reliability

All data stored or processed by the app is kept secure and private, adhering to ethical data handling standards. Personally identifiable information (PII) is not collected unless explicitly permitted. The system is fully functional offline, and no images or data are uploaded without user consent. This design ensures usability in rural settings while respecting user autonomy and privacy.

Physical Environment & Resources

Users are primarily CAO staff and local farmers requiring early disease detection for banana leaves and treatment

Software and Hardware Resources for Developers

Software:

- AI Development: Python, TensorFlow, OpenCV
- Mobile Development: Flutter, Dart, Android Studio
- Tools: Git, Firebase, Figma

Hardware:

- Workstation: Minimum Intel Core i3 (10^{th} Gen) or AMD Ryzen 5, 16GB RAM, 512GB SSD
- Test devices: Oppo A3s, OnePlus Nord, Xiaomi Redmi Note 12 Pro

Software and Hardware Resources for End Users

Software:

- AI-Based Banana leaf disease detector

Hardware:

- Device: Mobile phone (Android 9+, 2GB RAM, 50MB Free space)
- Internet: Full offline functionality

Development Cost

Box 1

Software Cost

Software	**Cost**
TensorFlow	Free
Visual Studio Code	Free
Android Studio	Free
Flutter	Free
Dart	Free

This box shows all the open-source software tools used in this capstone project. TensorFlow trains and optimizes our ResNet50 model for the banana disease detection. Visual studio serves as a code editor for Flutter and Dart extensions. Lastly, Android Studio's role is the IDE for app testing and debugging.

Box 2

Hardware Cost

Hardware	Cost
Developer PC (3)	₱70,000
Mobile phone for Testing	₱12,879
Internet Plan (3)	₱3,897

This box shows the hardwares and the internet plan involved in making the AI based banana leaf disease detector. The PCs are used to develop and train the AI itself and to develop the mobile app on Flutter, Dart and Android Studio. ISPs such as PLDT and Converge are used, priced at a monthly plan of 1,299. All these components serve as an important part of developing the AI-based system.

Box 3

Total Cost

Category	Total Cost
Software	₱0
Hardware	₱86,758
Grand Total	₱86,758

This box sums up all the costs from the Software and Hardware involved in making the system. While the Software costs 0 Pesos in total, the Hardware used by the developers is approximately 86,758 Pesos.

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