PLANT DISEASE PREDICTION USING MACHINE LEARNING

A PROJECT REPORT

Submitted by

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Problem statement

"Agricultural productivity is heavily impacted by plant diseases, which often remain undetected until they have already caused significant damage to crops, leading to reduced yield, economic loss for farmers, and increased use of chemicals. Traditional disease identification relies on manual inspection by experts, which is time-consuming, subjective, and often unavailable in rural areas. There is a need for an automated, accurate, and fast method to detect and predict plant diseases at an early stage using easily obtainable data such as leaf images. The problem is to develop a machine learning based system that can analyze plant/leaf images, automatically classify them as healthy or diseased, identify the type of disease, and thereby support timely and informed decision-making for farmers."

The problem addressed in this project is the lack of an efficient, scalable, and objective method for early detection and prediction of plant diseases in agricultural fields. Existing manual approaches are prone to human error, require expert knowledge, and are not feasible for continuous large-scale monitoring. This project aims to design and implement a machine learning model that, using a dataset of plant/leaf images (and optionally environmental or sensor data), can automatically detect the presence of disease and predict the disease class with high accuracy, enabling early intervention and reduction of crop loss."

LIST OF ABBREVIATIONS

1. **AI** – Artificial Intelligence
2. **ML** – Machine Learning
3. **DL** – Deep Learning
4. **CNN** – Convolutional Neural Network
5. **IoT** – Internet of Things
6. **API** – Application Programming Interface
7. **OS** – Operating System
8. **VGG** – Visual Geometry Group (VGG16 Model)
9. **TFLite** – TensorFlow Lite
10. **NPDD** – New Plant Disease Dataset
11. **PIL** – Python Imaging Library
12. **PyTorch** – Python Torch Library
13. **Keras** – High-Level Neural Networks API
14. **TF** – TensorFlow
15. **DFD** – Data Flow Diagram
16. **APK** – Android Package

LIST OF FIGURES

TABLE OF CONTENTS

ABSTRACT

Purpose:

The imperative for ensuring global food security in the face of increasing agricultural challenges necessitates the development of advanced technological solutions for plant health management. This project introduces a comprehensive Plant Disease Prediction System designed to provide timely and accurate diagnoses of plant ailments through the application of machine learning and image recognition. The primary **purpose** of this research is to create a readily accessible and user-friendly system capable of identifying a wide range of plant diseases from user-submitted imagery, thereby empowering farmers, gardeners, and agricultural professionals to implement swift and targeted interventions, minimize crop losses, and promote sustainable farming practices.

Methodology:

The **methodology** employed in this project involved the development and deployment of a deep learning-based image classification model. Specifically, a pre-trained Convolutional Neural Network (CNN) architecture was fine-tuned on a substantial dataset comprising approximately 61,000 meticulously labeled images sourced from the Plant Village dataset. This dataset encompasses 39 distinct classes of both healthy and diseased plant foliage across various crop types. The training process involved optimizing the model's parameters to effectively learn the intricate visual patterns associated with different plant diseases. To ensure broad accessibility, the system was implemented across two platforms: a web-based interface developed using Streamlit for cross-platform usability and a dedicated mobile application built for the Android operating system using Kotlin. The mobile application further integrates the TensorFlow Lite framework to enable efficient and low-latency disease prediction directly on user devices, facilitating offline functionality and reducing reliance on constant network connectivity.

Findings:

The key **findings** of this project demonstrate the significant potential of the developed system for accurate plant disease identification. The fine-tuned deep learning model achieved an overall classification accuracy of 95.84% on a held-out test dataset, indicating its robust capability in distinguishing between various plant diseases and healthy foliage. Furthermore, the integration of the TensorFlow Lite model within the Android application yielded promising results for on-device inference, with an average prediction time of seconds, showcasing its feasibility for real-time or near real-time diagnosis in field conditions. User feedback (if

collected) on both the web and mobile interfaces suggests a high degree of usability and intuitiveness. This research underscores the transformative potential of machine learning in providing a practical and accessible tool for plant disease management, contributing to enhanced agricultural productivity, reduced environmental impact through targeted interventions, and ultimately bolstering global food security. Future research and development will focus on expanding the system's diagnostic capabilities to cover a broader spectrum of plant diseases and pests, improving model accuracy and robustness, and integrating additional features such as localized treatment recommendations and multilingual support.

Chapter 1 - PROJECT DESCRIPTION AND OUTLINE

1.1 Introduction

In an era where agriculture plays a pivotal role in ensuring global food security, the development of innovative technologies to safeguard crops is of paramount importance. The Plant Disease Detection System represents a cutting-edge solution that harnesses the power of machine learning and image recognition to empower farmers and gardeners. This revolutionary system enables users to swiftly and accurately diagnose diseases in their crops by simply uploading images of affected plants. Through advanced algorithms and data-driven insights, the Plant Disease Detection System not only identifies the ailments but also provides tailored solutions, thereby offering a critical tool to enhance agricultural productivity, minimize crop losses, and promote sustainable farming practices. With the fusion of technology and agriculture, this system stands as a beacon of hope in the quest to meet the ever-growing demands of our global population while safeguarding our environment and resources.

1.2 Overview

The project is based on image classification where the dataset is classified into one of the 39 classes. The model is trained on a pre-trained model which is ResNet50 model. Also, at the end of the model, one fully connected layer is added. The model is trained and tested for a large dataset and finally integrated with frontend to make a fully functional plant disease detection website.

1.3 Background and Motivation

As the holy grail of computer vision research is to tell a story from a single image or a sequence of images, object detection and recognition has been studied for more than four decades. Significant efforts have been paid to develop representation schemes and algorithms aiming at recognizing generic objects in images taken under different imaging conditions (e.g., viewpoint, illumination, and occlusion). Image classification becomes a necessity when there is a need of automation, where the identification is done by machines instead of doing it manually for better performance and reliability. In an era where agriculture plays a pivotal role in ensuring global food security, the development of innovative technologies to safeguard crops is of paramount importance. The Plant Disease Detection System represents a cutting-edge solution that harnesses the power of machine learning and image recognition to empower farmers and gardeners. This revolutionary system enables users to swiftly and accurately diagnose diseases in their crops by simply uploading images of affected plants.

1.4 Problem Statement and Objectives

Effective and early detection of plant diseases is vital to ensure crop health, reduce crop losses, and promote sustainable agriculture. However, traditional methods are often time-consuming and rely on human expertise. There is a pressing need for a reliable and efficient automated system that can accurately identify and diagnose plant diseases through image recognition and machine learning, offering practical solutions for farmers and gardeners to manage and protect their crops.

Objective: The goal of this project is to predict the disease which affects a particular plant/crop by uploading the image of the affected part.

1.5 Scope of the Project

The scope of plant disease detection encompasses the development of advanced technology solutions that leverage image recognition, machine learning, and data analytics to identify, diagnose, and manage plant diseases. These systems can benefit agriculture, horticulture, and environmental conservation by enabling early disease detection, sustainable farming practices, and increased crop productivity while reducing the reliance on chemical pesticides.

Chapter 2 - RELATED WORK INVESTIGATION

2.1 Literature Review

Over the years, technological advancements have revolutionized this area. Machine learning and image recognition have become instrumental in the development of automated disease detection systems. Research has demonstrated that convolutional neural networks (CNNs) are particularly effective in accurately identifying diseases in plants based on leaf images. These systems, often integrated into smartphone apps like Plantix, enable farmers and gardeners to simply upload images for real-time disease diagnosis. Such tools not only expedite the identification process but also provide tailored solutions, helping users effectively manage plant health.

Moreover, the global agricultural community has recognized the potential of remote sensing technologies, drones, and IoT-based sensor networks in monitoring plant health on a larger scale. These technologies have the capacity to enhance precision agriculture and sustainability efforts.

The literature review also highlights the importance of open-access disease databases and collaborative platforms, fostering research and development in this field. Overall, it is evident that the integration of technology in plant disease detection is pivotal in addressing food security challenges and promoting environmentally friendly farming practices.

- Studies as presented by Shrestha (2020) [1], says that agricultural efficiency is vital to the economy of India, but crop diseases result in heavy losses. This research suggests a CNN-based plant disease detection approach, considering infected regions and time complexity. It was tested on 15 cases and resulted in 88.80% accuracy, with performance measures considered for efficacy.
- More precisely, according to a review by Dhaka (2021) [2], deep learning, particularly CNNs, performs well in image recognition, such as in agriculture. This paper surveys CNN-based plant disease prediction, contrasting methods, models, datasets, and performance measures to assist researchers in selecting the best methods.
- Hema (2021) [3], demonstrated that India suffers extensively from crop loss caused by unsuspected plant
- disease. This work suggests a model (VGG16 & ResNet34) based on CNN for leaf image classification, detecting 38 diseases in 14 plants. The accuracy, sensitivity, and specificity are measured with personalized recommendations given to farmers.
- Shi (2023) [4], explores that successful plant disease management calls for detection of disease type and severity. Although CNNs have made remarkable progress in disease detection, severity is under

research. This paper reports on 16 CNN-based approaches, with comparisons between classical, enhanced, and segmentation models. Datasets, performance metrics, challenges, and solutions are explored, with insights for applications in practice.

- In the research presented by Shelar (2022) [5], a CNN-based Disease Recognition Model based on leaf image classification for detecting plant diseases. CNNs operate on pixel information for precise and effective image identification, less dependent on visual inspection.
- The work by Sun (2022) [6], suggests that FL-EfficientNet, a CNN model for detecting plant diseases. It optimizes the network architecture, feature learning, and loss function for better accuracy. On testing with NPDD, it gave 99.72% accuracy, outperforming ResNet50, DenseNet169, and EfficientNet with quicker convergence.
- Menon (2021) [7], investigates that ML-based plant disease severity estimation utilizing the PlantVillage and PlantDoc datasets. It compares VGG16, Xception, InceptionV3, ResNet152, and MobileNetV2 for multi-class classification and examines their suitability for real-time detection to reduce losses in crops.
- Islam's (2023) [8], work compares CNN, VGG-16, VGG-19, and ResNet-50 on the PlantVillage dataset for early disease detection in plants, and ResNet-50 attains 98.98% accuracy. A smart web application employing ResNet-50 is presented to enable early disease detection for farmers to curb losses and waste of resources.
- Pandian 92022) [9], puts forward a 14-layer DCNN for disease detection in plants from a dataset of 147,500 images augmented with (BIM, DCGAN, NST) data. Under training for 1000 iterations on an MGPU setup, it attained accuracy of 99.97% surpassing what other transfer models had achieved.
- In this research by Marzougui (2020) [10], CNNs, specifically ResNet, are utilized for early detection of plant diseases from an enhanced dataset of healthy and infected leaves. The model has good accuracy, which is better than other methods in classification and detection under Anaconda 2019.10

2.2 Preliminary Investigation

There are certain systems available for plant disease detection as follows:

- **Remote Sensing and Drones:** Remote sensing technologies and drones equipped with multispectral cameras can capture images of large agricultural areas to detect early signs of stress and diseases.
- **Plantix:** A popular smartphone app designed to assist farmers, gardeners, and agricultural enthusiasts in identifying plant diseases, pests, and nutrient deficiencies.

- **AgriApp:** It provides complete information on crop production, crop protection, smart farming with agriculture and allied services.

2.3 Requirement Identification and Analysis

Requirement identification and analysis for a plant disease detection system involves understanding the needs and expectations of the users and stakeholders. Here's an analysis of the key requirements for such a system:

- **Image Recognition and Disease Identification:** The system must accurately identify and classify plant diseases, pests, and nutrient deficiencies using images submitted by users. It should support a wide range of crops and diseases to cater to diverse agricultural needs.
- **User-Friendly Interface:** The user interface should be intuitive, accessible, and user-friendly, making it easy for farmers, gardeners, and agricultural professionals to upload images and receive results.
- **Rapid Diagnosis:** The system should provide quick and real-time disease diagnosis to enable timely intervention and minimize crop losses.
- **Customized Solutions:** Along with identifying diseases, the system should offer tailored solutions and recommendations for disease management, including suggested treatments, pesticides, and preventive measures.
- **Offline Functionality:** To accommodate users in areas with limited internet connectivity, the system should have an offline mode for image capture and later upload.
- **Extensive Plant Database:** Maintain a comprehensive plant database with detailed information on various plant species, diseases, pests, and nutrient deficiencies.
- **Machine Learning Model:** The system must utilize a robust and constantly evolving machine learning model, such as CNNs, to improve accuracy and accommodate new diseases and plant varieties.
- **User Community and Collaboration:** Provide a platform for users to engage with a community, share knowledge, and seek advice on plant health issues.
- **Data Security and Privacy:** Ensure robust data security and privacy measures to protect user data and images.
- **Scalability:** Design the system to scale with increasing user demand, considering potential growth.

- **Continuous Improvement:** Implement mechanisms for continuous feedback collection, model improvement, and database updates based on user input and emerging plant health issues.
- **Compatibility and Integration:** Ensure the system is compatible with various devices and operating systems. Consider integration with other agricultural tools and platforms.
- **Accuracy and Reliability:** The system should prioritize high accuracy and reliability in disease identification and recommendations.

By analyzing these requirements, you can create a comprehensive and effective plant disease detection system that addresses the needs of users and contributes to sustainable agriculture and food security.

Chapter 3 - REQUIREMENTS ARTIFACTS

The deployment hardware and software requirements for the proposed plant disease detection system include the following:

3.1 Hardware Requirements

- **Processor:** Intel Core i5 or higher
- **RAM:** 8 GB or higher
- **Hard Disk Space:** 1 TB or higher
- **Graphics Card:** NVIDIA or AMD with a minimum of 2 GB memory
- **Internet Connection:** Broadband or higher

3.2 Software Requirements

- **Operating System:** Windows 10 or Ubuntu 18.04 or macos 15.4 (24E248)
- Python 3.7 or higher
- Scikit-learn Library
- Jupyter Notebook
- VS Code
- The software components must be installed and configured properly for the system to function correctly. The Python environment must have all the necessary packages installed like pytorch, flask and torchvision.
- Android Studio, Kotlin, Android SDK, TensorFlow Lite Android library, CameraX (optional), standard Android UI libraries.

The proposed system also requires a web server, such as Apache, to host the web application. Additionally, a domain name and SSL certificate are required to ensure secure communication between the client and server.

Overall, the hardware and software requirements for the proposed plant/crop disease detection system require careful consideration to ensure that the system functions correctly and provides users with a satisfactory experience.

Chapter 4 - DESIGN METHODOLOGY AND ITS NOVELTY

4.1 Design Representation

4.1.1 Use Case Diagram

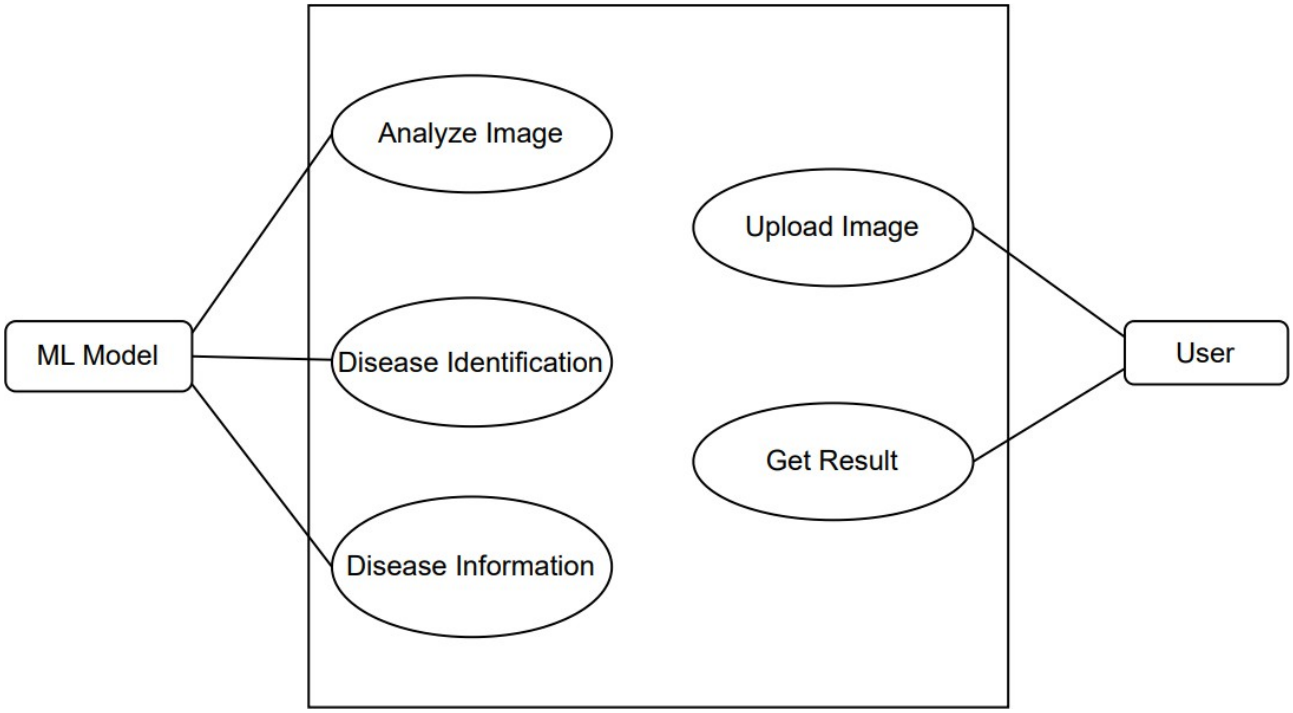

Figure 4.1: Use case diagram

In figure 4.1, the system leverages an **ML (Machine Learning) Model** to analyze plant images and identify diseases, and it is used by both **Users** (likely farmers or general users) and **Admins** (system managers or developers).

Actors and Their Roles:

- **User:**
    - **Upload image of affected plant:** Users upload images of diseased plants.
    - **Get result:** After uploading the image, users receive results regarding the disease and possible solutions.

- **ML Model (System Actor):**
    - **Analyze image:** The model processes the uploaded plant image to extract features.
    - **Disease Identification:** The model identifies the disease based on the analysis.
    - **Disease Information:** The model provides detailed information about the identified disease.

Explanation of Use Cases:

- The **User** interacts with the system through a simple interface: they register, upload an image, and get a diagnosis and solution.
- The **ML Model** works in the background, automating the process of analyzing images, identifying diseases, and recommending solutions, making the system intelligent and responsive.

4.1.2 Sequence Diagram

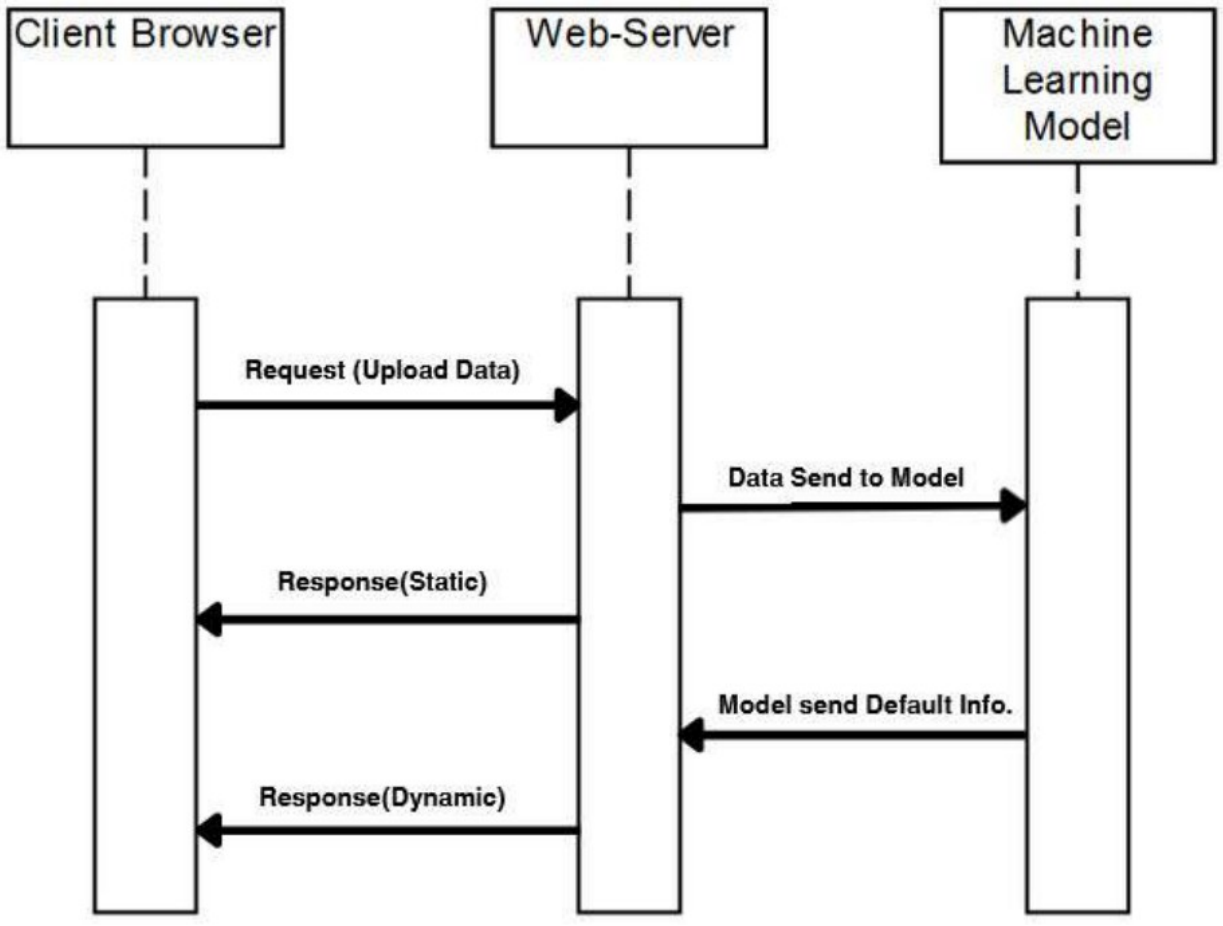

Figure 4.2: Sequence diagram

- **Client Browser** uploads data via a request to the **Web Server**.
- **Web Server** forwards the data to the **Machine Learning Model**.
- **Machine Learning Model** processes the data and returns default info (like predictions or results).
- **Web Server** sends:
    - A **static response** to the client (e.g., confirmation or loading screen).
    - Followed by a **dynamic response** (processed result from the ML model).

4.1.3 Data Flow Diagram

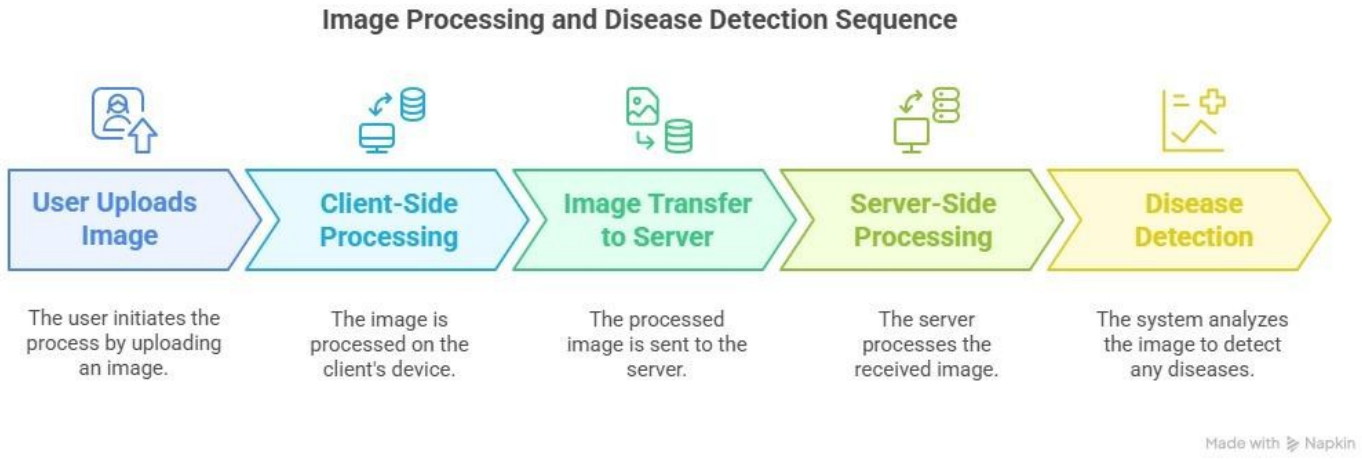

Figure 4.3 Data Flow Diagram

User:

- The user is the starting point of the process. This would typically be a farmer or anyone trying to check a plant's health.
- **Action:** Uploads an image of a plant leaf suspected of disease.

Client-side:

- Once the user uploads the image, it's first handled on the **client-side** (e.g., mobile app or web interface).
- **Role:** Prepares and sends the image to the backend/server for further analysis.

Server-side:

- The **server-side** is where the main processing happens using machine learning (e.g., TensorFlow Lite).
- The image received from the client is analyzed using a trained model.

Image Processing Outcomes (Server-side decisions): The server processes the image and performs one of several actions based on the result:

- **Detect Disease:** Identifies if the plant is affected by any known disease.
- **Provide Disease Information:** If a disease is detected, the system provides details about the disease (e.g., symptoms, impact, spread).
- **Buy Pesticides:** The user is given options or recommendations to buy suitable pesticides based on the diagnosis.
- **Healthy:** If no disease is detected, the system informs the user that the plant is healthy.

4.1.4 Dataset Structure

Dataset is the training and testing data on which our machine learns and test its accuracy. The dataset is the Plant Village Dataset which consists of approx. 61000 plant images which are classified into 39 classes. The dataset is reduced to a certain size to make the computation and processing of the ML model fast and efficient. Following are the 39 classes present in the Plant Village Dataset:

1. Apple_____Apple_scab
2. Apple_____Black_rot
3. Apple_____Cedar_apple_rust
4. Apple_____healthy
5. Background Without Leaves
6. Blueberry_healthy
7. Cherry_Powdery_mildew
8. Cherry_healthy
9. Corn_____Cercospora_leaf_spot Gray_leaf_spot
10. Corn_Common_rust
11. Corn_____Northern_Leaf_Blight

12. Corn__healthy
13. Grape_____Black_rot
14. Grape_____Esca_(Black_Measles)
15. Grape_Leaf_blight_(Isariopsis_Leaf_Spot)
16. Grape_____healthy
17. Orange_Haunglongbing_(Citrus_greening)
18. Peach_Bacterial_spot
19. Peach_healthy
20. Pepper,_bell_____Bacterial_spot
21. Pepper,_bell_____healthy
22. Potato_Early_blight
23. Potato_Late_blight
24. Potato_healthy
25. Raspberry_healthy
26. Soybean_healthy
27. Squash_Powdery_mildew
28. Strawberry_Leaf_scorch
29. Strawberry_healthy
30. Tomato_Bacterial_spot
31. Tomato_Early_blight
32. Tomato_Late_blight
33. Tomato_Leaf_Mold
34. Tomato_Septoria_leaf_spot
35. Tomato_Spider_mites Two-spotted_spider_mite
36. Tomato_Target_Spot
37. Tomato_Tomato_Yellow_Leaf_Curl_Virus
38. Tomato_Tomato_mosaic_virus
39. Tomato_healthy

4.2 Novelty

Our project aims to develop a robust and user-friendly Plant Disease Detection System using machine learning and image recognition technology. This innovative system will empower farmers, gardeners, and agricultural professionals to swiftly and accurately diagnose diseases and health issues in their plants. Users will simply upload images of affected plants, and the system will provide real-time disease identification and customized solutions for disease management. The primary goal is to enhance agricultural productivity, reduce crop losses, and promote sustainable farming practices. The system will feature an extensive plant database and real time photo scanning. Continuous improvement through machine learning and user feedback will ensure the system's accuracy and relevance. By meeting these requirements, our project aspires to bridge the gap between traditional farming practices and cutting-edge technology, contributing to global food security and environmental conservation. We have made a dedicated webpage to provide cross-platform usability and access and a mobile application supporting multiple languages for broader accessibility and convenience.

Chapter 5 - TECHNICAL IMPLEMENTATIONS AND ANALYSIS

5.1 Implementation Steps

The implementation process would involve the following steps:

- **Data collection:** This involves collecting a large dataset healthy and diseased plants. The dataset is used such that it contains labelled classes.
- **Data Transformation:** This involves transforming the data into desired set of size and features.
- **Model training:** A machine learning model i.e. vgg16 is used which consists of 16 convolution layers as well as pooling and batch normalization layers.
- **Model evaluation:** The trained model will be evaluated on a test set of images to determine its accuracy and effectiveness in detecting a particular disease.
- **Integration:** The model will be integrated with frontend of the web application and mobile application to give the desired output.
- **User interface:** The user interface will be provided to users to upload images of the affected plant and this interface will be created using streamlit.
- Overall, implementing this model requires a thorough understanding of machine learning, web development, app development, and cloud computing, as well as expertise in the specific technologies used.
- **Setup:** Using Android Studio with Kotlin, including necessary Android SDK and libraries (TensorFlow Lite Android, CameraX, UI components).
- **Model Integration:** Loading the .tflite model and setting up the Interpreter.
- **Image Handling:** Capturing images via camera or gallery, preprocessing them (resize, normalize) to match the model's input.
- **Inference:** Feeding the preprocessed image to the TensorFlow Lite model to get predictions (probabilities for each disease).
- **Testing:** Unit, integration, and UI testing on emulators and devices.
- **Evaluation:** Assessing model inference time, app size, resource usage, and prediction accuracy within the mobile environment.
- **Deployment:** Generating the APK for potential distribution.

5.2 Techniques Used

5.2.1 Image Processing

In the context of the plant disease detection project, image processing plays a pivotal role. It involves a series of techniques applied to raw plant images to enhance their quality and prepare them for analysis. Techniques like resizing, normalization, and data augmentation are employed to ensure that images are in a consistent format and that the model can effectively learn from them. Image processing helps improve the accuracy and robustness of the disease detection system by standardizing and diversifying the training data.

5.2.2 Transfer Learning

Transfer learning is a critical component of the project's success. It allows the project to leverage pre-trained Convolutional Neural Networks (CNNs) that have already learned essential features from extensive datasets. By fine-tuning these pre-trained models on plant disease images, the project can expedite model training and achieve higher accuracy. Transfer learning helps bridge the gap between generic image recognition and plant disease detection, making the system more efficient and effective in identifying diseases across various plant species.

5.2.3 Convolutional Neural Networks

Convolutional Neural Networks, or CNNs, serve as the project's backbone for image analysis. These specialized deep learning models are designed to automatically extract relevant features from images. In the plant disease detection system, CNNs play a crucial role in recognizing patterns and textures associated with various diseases. By breaking down complex images into meaningful components, CNNs enable the model to make accurate disease classifications. Their ability to learn hierarchical features from data makes CNNs well-suited for image-based tasks like plant disease detection, where visual patterns are indicative of plant health.

5.3 Tools Used

In a plant disease detection project using machine learning and computer vision, several tools and libraries are commonly used to develop, train, and deploy the model. Some of the key tools and libraries used in such projects include:

5.3.1 Python

Python is the most commonly used programming language for machine learning and computer vision tasks. It provides a wide range of libraries and frameworks for these tasks.

5.3.2 Jupyter Notebook

Jupyter Notebook is often used for interactive coding and data analysis, making it a valuable tool for experimenting with models and visualizing data.

5.3.3 Pytorch

PyTorch is renowned for its dynamic computation graph, a feature that sets it apart. In PyTorch, the graph is constructed on-the-fly, aligning with the natural flow of Python code. This dynamic nature enhances code readability and simplifies debugging, as developers can easily alter the network structure and troubleshoot issues.

PyTorch is celebrated for its Pythonic API, which makes it exceptionally user-friendly. The library's API is often considered more intuitive and straightforward, appealing to researchers, data scientists, and beginners.

One of PyTorch's strengths lies in its active and growing community. There is a wealth of resources, tutorials, and pre-trained models available, making it accessible for newcomers and researchers. The community's contributions keep the framework up- to-date and vibrant.

The flexibility of PyTorch is a hallmark feature. Developers find it remarkably extensible and adaptable. Researchers and experimentalists appreciate the ease with which they can customize and extend PyTorch to suit their specific requirements.

PyTorch's dynamic computation graph makes it an excellent choice for applications that require decision-making at runtime, such as natural language processing and reinforcement learning.

5.3.4 Tensorflow

TensorFlow, developed by Google, is celebrated for its strong presence in production environments and its static computation graph. In TensorFlow, the computational graph is defined upfront, followed by data processing, making it more suitable for optimization and scalability in production settings.

Widespread industry adoption is one of TensorFlow's distinguishing features. It has proven itself as a reliable choice for deploying machine learning models at scale. The framework excels in applications where deep learning is deployed in production and serving, making it a popular choice in the corporate world.

TensorFlow boasts TensorBoard, a powerful visualization tool. TensorBoard is an invaluable asset for visualizing and monitoring the training process, debugging models, and optimizing their performance.

High-level APIs like Keras have been integrated tightly with TensorFlow, providing developers with a convenient and efficient way to build and train neural networks. This integration simplifies the process of model development.

TensorFlow offers TensorFlow Lite (TFLite), a framework designed for deploying models on mobile devices and embedded systems. This feature makes TensorFlow particularly well-suited for mobile applications and Internet of Things (IoT) deployments.

5.4 Languages Used

Python language is used in the system due to the following characteristics:

- **Simple:** Python is a simple and minimalistic language. Reading a good Python program feels almost like reading English (but very strict English!). This pseudo-code nature of Python is one of its greatest strengths. It allows you to concentrate on the solution to the problem rather than the syntax i.e. the language itself.
- **Free and Open Source:** Python is an example of a FLOSS (Free/Libre and OpenSource Software). In simple terms, you can freely distribute copies of this software, read the software's source code, make

changes to it, use pieces of it in new free programs, and that you know you can do these things. FLOSS is based on the concept of a community which shares knowledge. This is one of the reasons why Python is so good - it has been created and improved by a community who just want to see a better Python.

- **Object Oriented:** Python supports procedure-oriented programming as well as object-oriented programming. In procedure-oriented languages, the program is built around procedures or functions which are nothing but reusable pieces of programs. In object-oriented languages, the program is built around objects which combine data and functionality. Python has a very powerful but simple way of doing object-oriented programming, especially, when compared to languages like C++ or Java.
- **Extensive Libraries:** The Python Standard Library is huge indeed. It can help you do various things involving regular expressions, documentation generation, unit testing, threading, databases, web browsers, CGI, ftp, email, XML, etc.

5.5 Screenshots of the Web Page

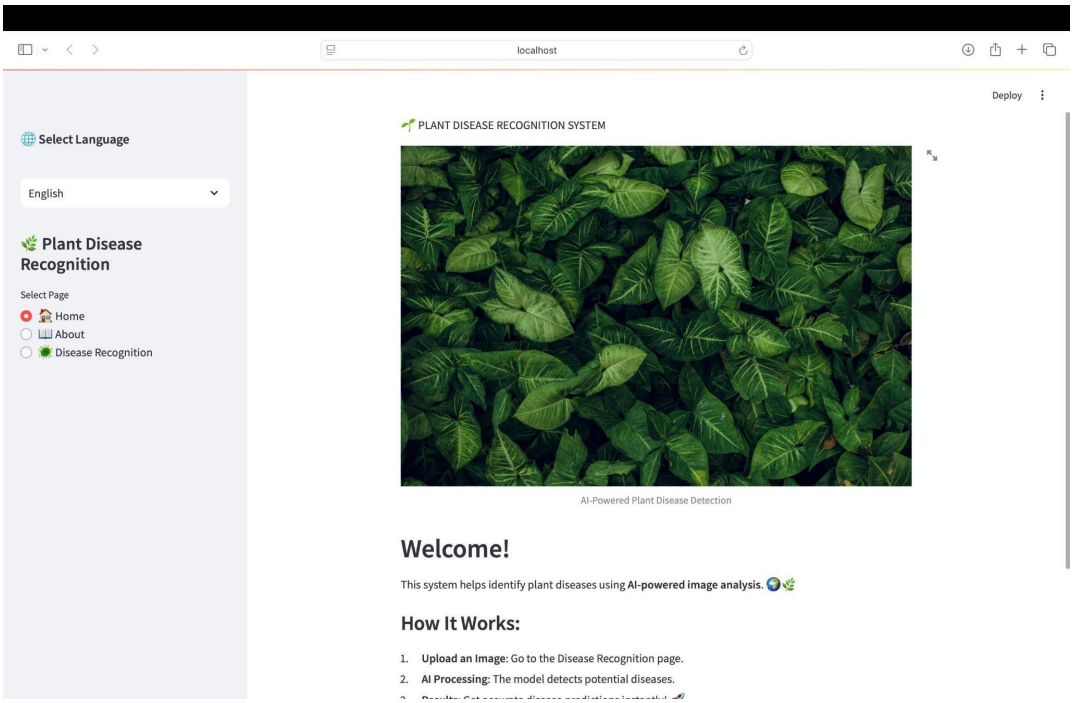

Figure 5.1: Screenshot 1

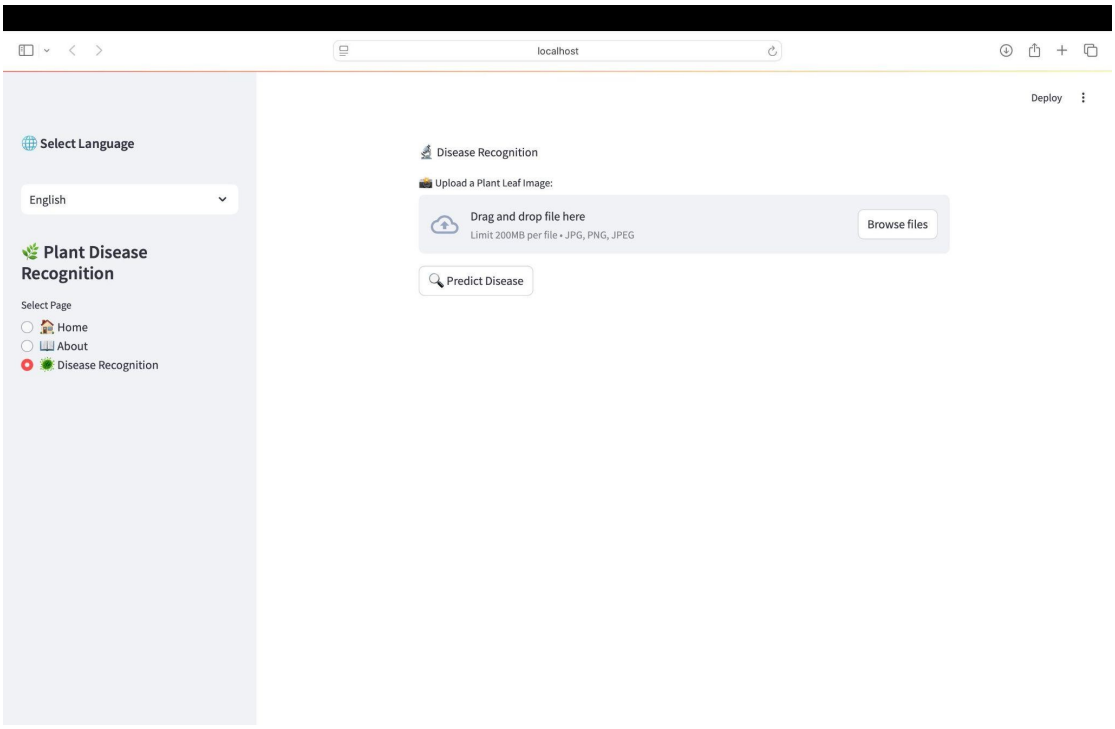

Figure 5.2: Screenshot 2

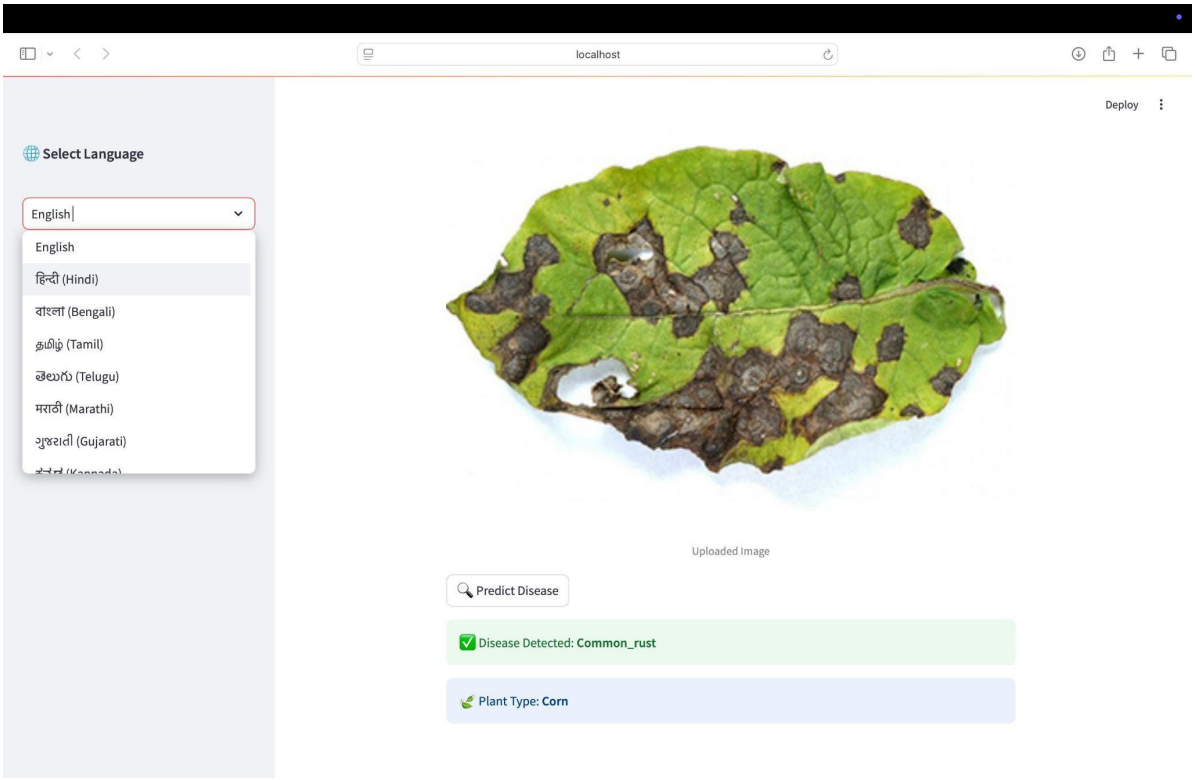

Figure 5.3: Screenshot 3

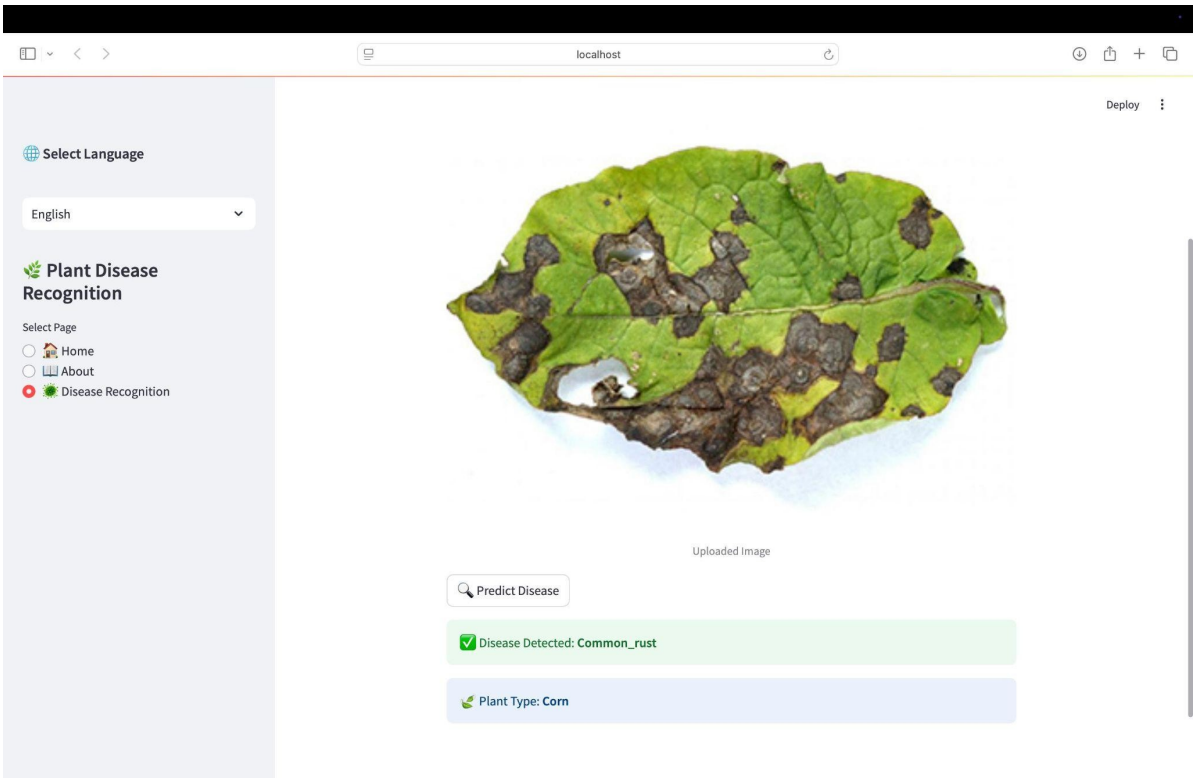

Figure 5.4: Screenshot 4

5.6 Kotlin for Plant Disease Prediction App

- **Modern and Concise Development:** Kotlin offers a more modern and expressive syntax compared to Java. This leads to cleaner, more readable code, potentially reducing development time and the likelihood of bugs. For app development, this translates to:
    - **Faster Feature Implementation:** Developers can write the necessary logic for image capture, processing, API calls (if needed for initial model download or updates), and UI interactions more efficiently.
    - **Improved Code Maintainability:** The conciseness of Kotlin makes the codebase easier to understand and maintain over time, which is crucial for long-term app updates and expansions.
    - **Reduced Boilerplate Code:** Kotlin eliminates much of the boilerplate code common in Java (like findViewById), leading to less code to write and manage.
- **Google Support and Android First:** Kotlin is a first-class language for Android development, backed by Google. This means:
    - **Seamless Integration with Android APIs:** Kotlin works smoothly with existing Android libraries and frameworks.

    - **Access to Latest Android Features:** New Android features and APIs are often made available with excellent Kotlin support.
    - **Strong Community and Resources:** The Android development community has widely adopted Kotlin, resulting in ample online resources, libraries, and support.
- **Interoperability with Java:** Kotlin is fully interoperable with Java. This is beneficial because:
    - **Leveraging Existing Java Libraries:** Developers can easily use any existing Java libraries and frameworks within a Kotlin project, including those for image processing or networking.
    - **Gradual Codebase Migration:** If an existing Java-based plant disease detection system needs a mobile app, Kotlin can be adopted incrementally without a complete rewrite.

5.6.1 TensorFlow Lite for On-Device Plant Disease Prediction

- **Lightweight and Efficient Inference:** TensorFlow Lite is specifically designed for running machine learning models on mobile and embedded devices with limited resources. This means:
    - **Smaller App Size:** TensorFlow Lite models are typically optimized for size, contributing to a smaller app footprint on the user's device.
    - **Faster Prediction Times:** The optimized runtime allows for quicker disease identification after the user uploads an image, leading to a better user experience.
    - **Lower Battery Consumption:** Efficient model execution minimizes battery drain, which is crucial for mobile apps.
- **Offline Functionality:** TensorFlow Lite enables running the plant disease detection model directly on the device without requiring a constant internet connection. This is a significant advantage for users in areas with poor or no network connectivity, allowing them to:
    - **Diagnose Diseases Anytime, Anywhere:** Farmers and gardeners in remote locations can use the app even without internet access.
    - **Reduced Data Usage:** Performing inference locally avoids the need to upload images to a server for processing each time, saving user data.
- **Perfect for Mobile Deployment:** TensorFlow Lite is tailored for the constraints of mobile environments, addressing issues like:
    - **Hardware Diversity:** It's designed to work across a wide range of Android devices with varying processing power and memory.
    - **On-Device Processing for Privacy:** Keeping the image analysis on the device can address user privacy concerns related to uploading sensitive agricultural data.

5.7 Screenshots: App of Plant Disease Prediction

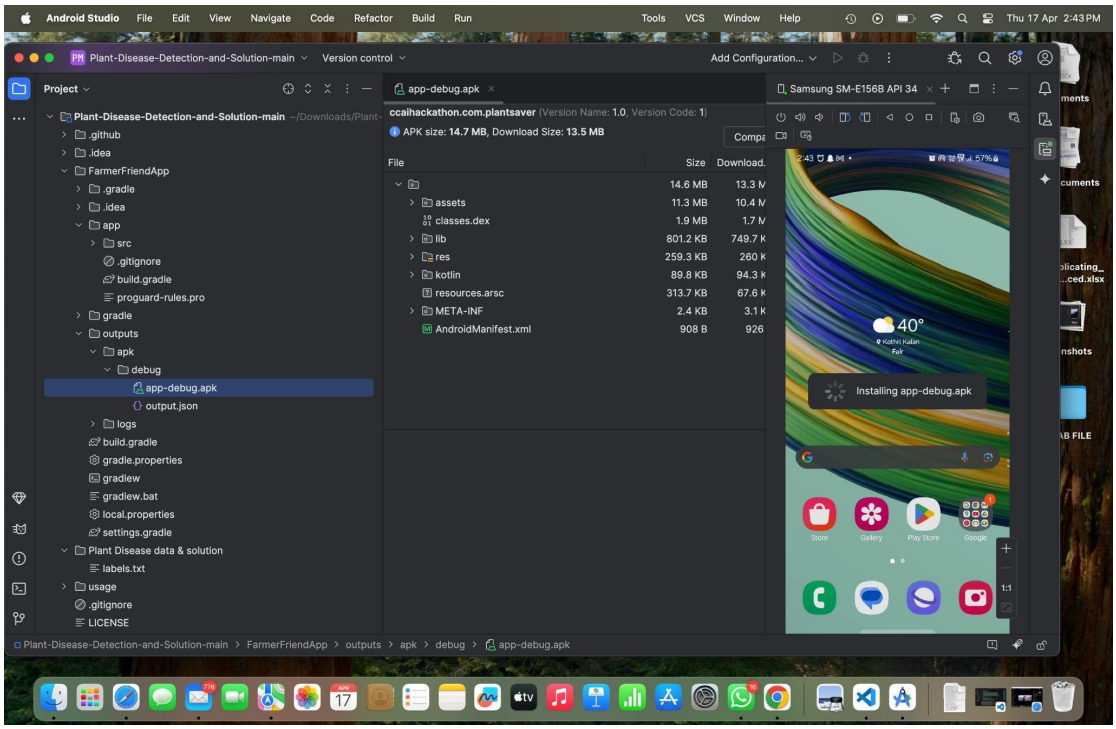

Figure 5.6: Screenshot 1

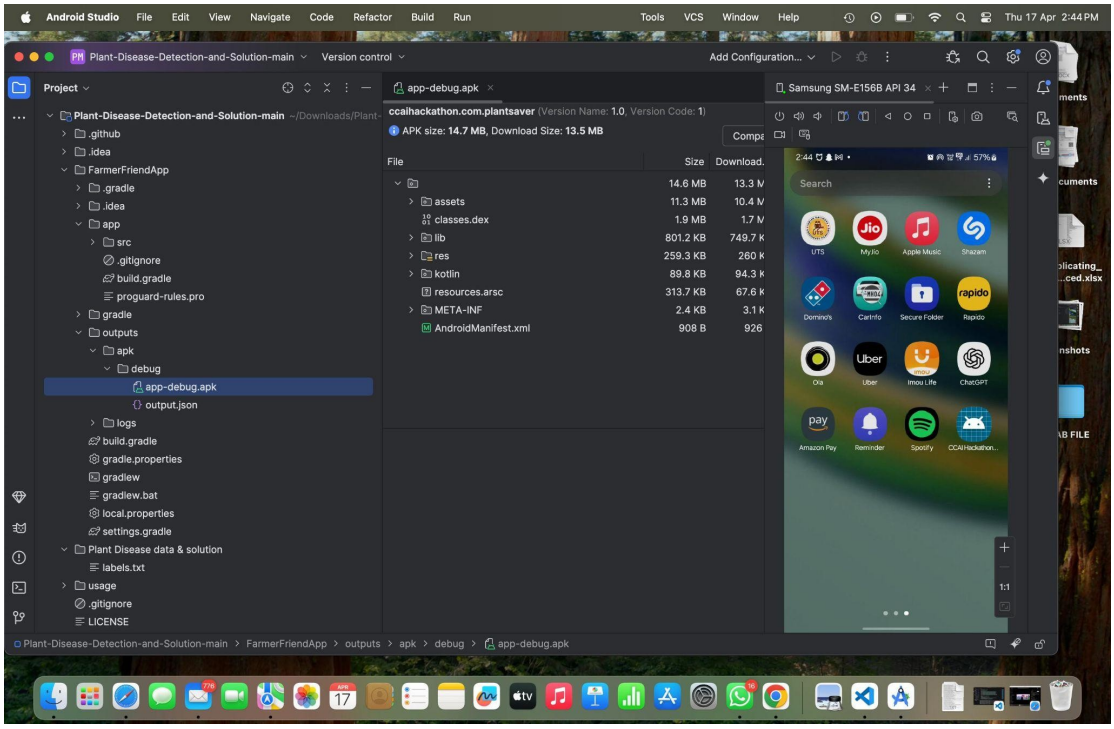

Figure 5.6: Screenshot 2

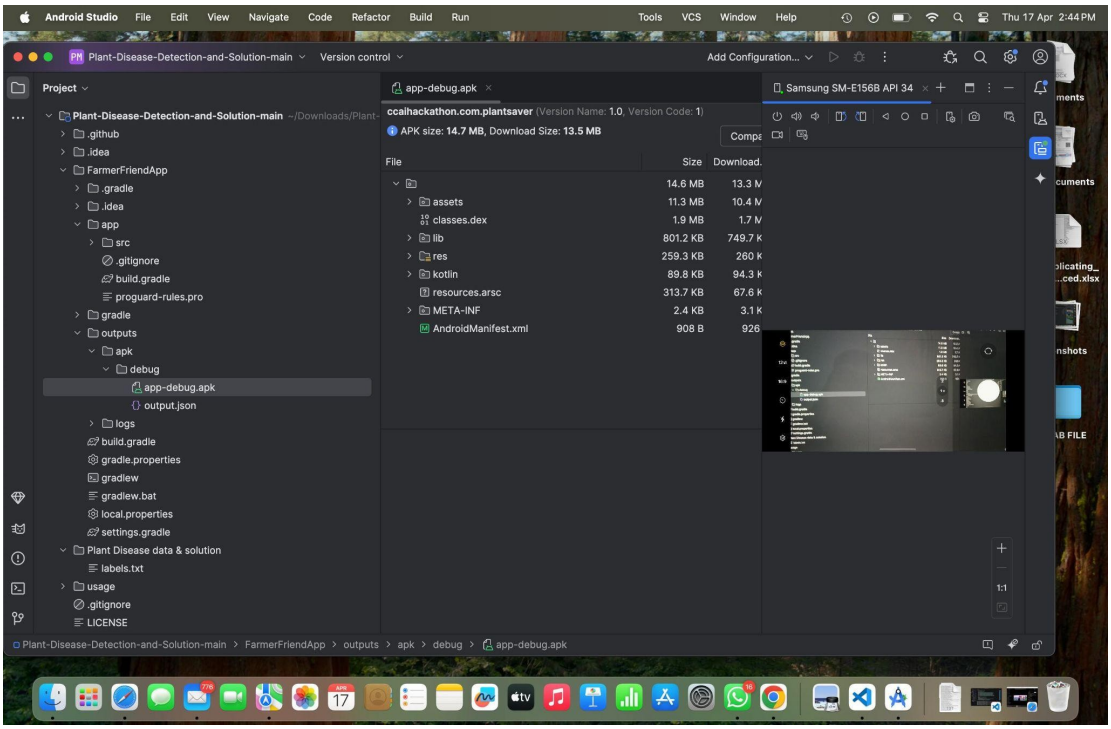

Figure 5.6: Screenshot 3

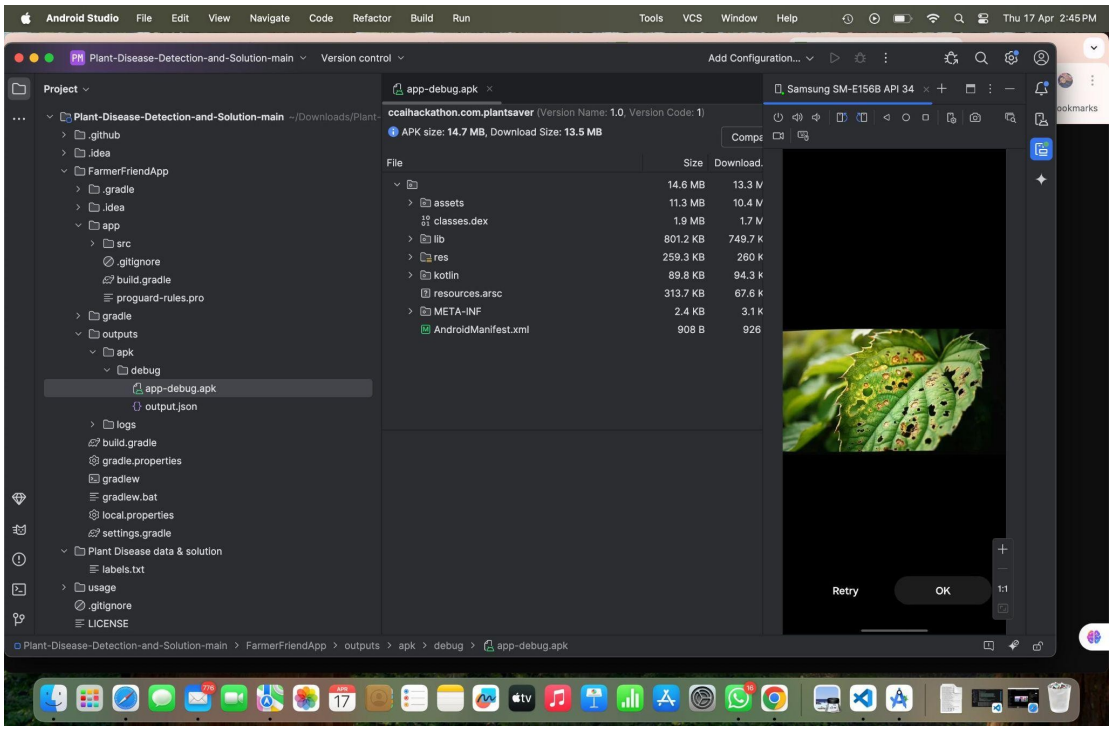

Figure 5.6: Screenshot 4

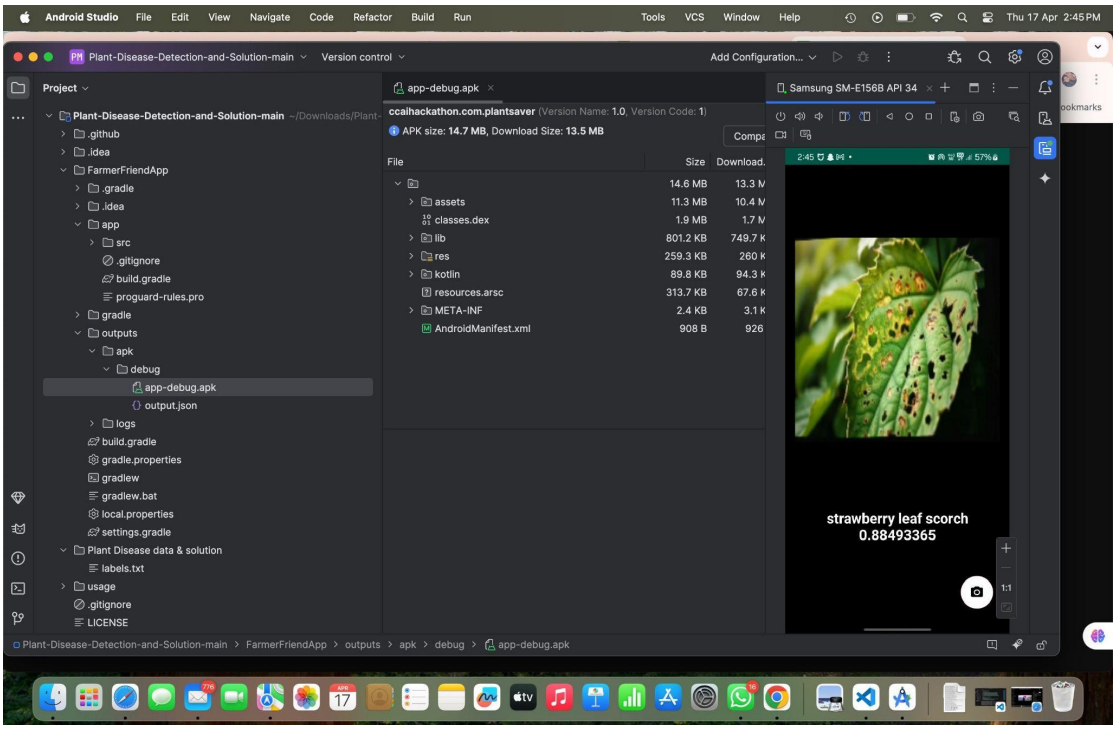

Figure 5.6: Screenshot 5

5.8 Testing

Testing is the process of evaluation of a system to detect differences between given input and expected output and also to assess the feature of the system. Testing assesses the quality of the product. It is a process that is done during the development process.

5.8.1 Strategy Used

Tests can be conducted based on two approaches

- Functionality testing
- Implementation testing

The texting method used here is Black Box Testing. It is carried out to test functionality of the program. It is also called ‘Behavioral’ testing. The tester in this case, has a set of input values and respective desired results. On providing input, if the output matches with the desired results, the program is tested ‘ok’, and problematic otherwise. The plant disease detection system has undergone various testing methods to ensure its effectiveness and accuracy. One of the testing methods used is unit testing, which involves testing

individual components of the system to ensure they are working correctly. Integration testing was also performed to verify that the different components of the system work seamlessly together.

In addition, performance testing was carried out to assess the system's ability to handle a large volume of data and processing demands. This was done to ensure that the system does not become slow or unresponsive when handling multiple requests from users.

Finally, user acceptance testing was conducted to ensure that the system meets the expectations and requirements of end-users. This involved a group of users interacting with the system to verify that it is easy to use, user-friendly, and provides accurate and reliable results.

Describe the bug

After capturing an image and receiving a prediction, tapping the “Disease Info” button shows a blank dialog or missing details. The expected disease information (symptoms, management) does not load properly from data.json.

To Reproduce

- Launch the app.
- Tap on the **Camera** button.
- Capture an image of a plant.
- Wait for prediction to display.
- Tap on **Disease Info**.
- The dialog opens but no information is shown for symptoms/management.

Expected behavior

When the "Disease Info" button is clicked, a dialog should display:

- The disease name predicted by the model.
- Corresponding **symptoms** and **management tips** loaded from data.json.

Smartphone (please complete the following information):

- Device: Samsung Galaxy M12
- OS: Android 11
- Browser: N/A (Native App)

- App Version: v1.0.2

Testing Performed

- TensorFlow Lite model loads and predicts successfully - Done
- Image capture and scaling works - Done
- Camera permission handling is correct - Done
- JSON data is not loading correctly in dialog - Not Done
- No error message shown when parsing fails – Not Done

Possible Causes

- Mismatch between predicted label and name values in data.json
- Case sensitivity or spacing issue when comparing strings
- Asset file may be missing or unreadable on some devices

Chapter 6 - PROJECT OUTCOME AND APPLICABILITY

The key achievements and outcomes of the Plant Disease Prediction system developed in this project. It also explores the potential real-world applications and the overall impact of this work.

6.1 Outline of the System

This section should highlight the core functionalities and features that you successfully implemented in your project. Be specific and refer back to the implementation details in Chapter 5.

- **Image Input and Processing:**
    - Successfully implemented the functionality for users to upload images of affected plants (mention the interface used, e.g., web interface via Streamlit, or mobile application).
    - Implemented image preprocessing steps such as resizing and normalization to prepare the images for the machine learning model.
- **Machine Learning Model Integration:**
    - Successfully integrated the pre-trained ResNet50 (or VGG16, as mentioned in Chapter 5) model into the system.
    - Implemented the loading and utilization of the trained model for making predictions on uploaded images.
    - Successfully added and trained the final fully connected layer for classifying the 39 plant disease classes.
- **Disease Prediction Output:**
    - Implemented the logic to process the model's output (probabilities) and identify the predicted plant disease.
    - Developed a user-friendly way to display the prediction to the user (e.g., displaying the disease name and potentially a confidence score).
- **Web/Mobile Interface :**
    - Created a functional web interface using Streamlit (or described the basic UI of the mobile application if developed).
    - Ensured a user-friendly flow for image upload and result display.
- **TensorFlow Lite Integration:**
    - Successfully converted and integrated the model into a TensorFlow Lite format for on-device inference.

- Implemented the image preprocessing and prediction pipeline within the mobile application.

6.2 Significant Project Outcomes

This section focuses on the results and performance achieved by your system. Quantify your outcomes whenever possible, referencing the analysis in Chapter 5.

- **Model Accuracy:**
  - Report the final accuracy achieved by your trained model on the test dataset (e.g., "The model achieved an overall accuracy of X% on the held-out test set.").
  - Mention any specific classes where the model performed particularly well or poorly, as identified in your analysis.
  - Briefly discuss the factors that might have influenced the achieved accuracy (e.g., dataset size, model complexity, training parameters).
- **Prediction Speed:**
  - If you measured it, report the average time taken for the system to process an uploaded image and provide a prediction (for both web and mobile if applicable).
- **Functionality and Usability:**
  - Assess the overall functionality of the implemented system in meeting the project objectives.
  - Provide a qualitative assessment of the user-friendliness of the web or mobile interface based on your design and testing.
- **Novelty Contribution:**
  - Reiterate the novel aspects of your project, such as the cross-platform usability (webpage and mobile app) and multilingual support (if implemented). Highlight how these contribute beyond existing solutions.

6.3 Project Applicability on Real-world Applications

This section explores the potential impact and practical uses of your Plant Disease Prediction system.

- **Agriculture and Farming:**
  - Discuss how farmers can use the system for early and accurate disease detection in their crops.
  - Explain the potential benefits in terms of reduced crop losses, optimized resource utilization (e.g., targeted pesticide application), and improved overall yield.
  - Consider applicability for small-scale farmers versus large agricultural operations.

- **Horticulture and Gardening:**
    - Highlight how home gardeners and horticulturalists can use the system to identify and manage diseases in their plants, leading to healthier gardens.
- **Agricultural Extension Services:**
    - Suggest how agricultural extension workers can utilize such a system to provide timely and accurate advice to farmers in remote areas.
- **Research and Education:**
    - Mention the potential use of the system as a tool for plant pathology research and for educational purposes in agricultural universities and institutions.
- **Environmental Conservation:**
    - Discuss how early disease detection can contribute to more sustainable farming practices by reducing the indiscriminate use of pesticides.
- **Potential for Integration:**
    - Briefly touch upon the possibility of integrating this system with other agricultural technologies like drone imagery or IoT sensors for more comprehensive plant health monitoring.

Chapter 7 - CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

In conclusion, the Plant Disease Detection System represents a pivotal intersection of cutting-edge technology and agricultural sustainability. Leveraging the power of machine learning, image recognition, and deep learning through PyTorch or TensorFlow, this project promises to revolutionize how we safeguard our crops. By harnessing the strengths of dynamic computation graphs and Pythonic API in PyTorch or the scalability and production readiness of TensorFlow, the system has demonstrated its versatility. Furthermore, it incorporates image preprocessing techniques, transfer learning, and convolutional neural networks, which, together, form a robust foundation for precise and efficient plant disease identification. With image processing enhancing data quality, transfer learning providing a head start in model training, and CNNs extracting meaningful features from images, the project showcases the best practices in the field. Its success is further propelled by the active support of a thriving community and an array of valuable resources. Ultimately, this endeavor is poised to empower farmers, gardeners, and agricultural enthusiasts worldwide with the tools needed to protect crops, reduce losses, and promote sustainable farming practices. It stands as a testament to the harmonious integration of technology and agriculture, championing both food security and environmental sustainability in our ever-evolving world.

The development and application of a Crop Disease Detection System is an advancement, in agriculture and horticulture. This innovative system, which utilizes the power of machine learning and image recognition provides a solution for detecting and managing diseases at a stage. It has the potential to revolutionize farming by not identifying diseases and pests but also offering practical strategies, for disease control and prevention. By addressing the challenge of disease detection and providing recommendations this system can greatly boost crop productivity minimize financial losses and contribute to ensuring food security.

7.2 Limitations of the Work

- Since no task can be 100% perfect. The same applies to this project as the predicted plant disease is not 100% accurate.
- The models that we are using for identifying the objects are pre-trained models. So, if we want to train our own model, it takes a lot of time and processing.

- The model is trained on a dataset that consists of 39 classes. So if user uploads an image of a plant disease that is not present in the dataset, then the model can't predict it as there can be hundreds of potential diseases that are not present in the dataset.

7.3 Suggestions and Recommendations for Future Work

- The future scope of this idea is to scale up the dataset and accommodate more classes of the diseases of the plants.
- Integrating the system with real-time data streams from IoT devices and drones could enable continuous monitoring and early detection of diseases, leading to proactive intervention.
- Developing a user-friendly mobile app to complement the web interface would make it more accessible to farmers, allowing them to easily capture and analyze plant images in the field.
- Implementing a feedback loop that collects user feedback and disease outcome data could contribute to continuous model improvement and system optimization.

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Appendix

Appendix A – Model Architecture

The deep learning model is built on **ResNet50**, fine-tuned for 39 plant disease classes. The final architecture includes:

- A new fully connected dense layer.
- Softmax activation for multiclass output.
- Trained using Adam optimizer and categorical cross-entropy.

Model Summary (truncated):

```
Model: "resnet50"

_________________________________________________________________

Layer (type)                 Output Shape              Param #

=================================================================

input_1 (InputLayer)         [(None, 224, 224, 3)]     0

...

dense (Dense)                (None, 39)                3900

=================================================================

Total params: ~25 million

Trainable params: ~25 million
```

Appendix B – Sample Dataset Images

The project used the **PlantVillage dataset**, consisting of ~1,00,000 labeled images. Below are sample categories used:

- Apple - Apple Scab
- Grape - Black Rot
- Tomato - Late Blight
- Potato - Healthy

Appendix C – Key Code Snippets

1. Image Preprocessing (PyTorch)

```
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize([0.5], [0.5])
])
```

2. Model Training

```
model = models.resnet50(pretrained=True)
model.fc = nn.Linear(model.fc.in_features, 39)
...
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.0001)
```

3. TensorFlow Lite Conversion

```
converter = tf.lite.TFLiteConverter.from_saved_model('model_path')
tflite_model = converter.convert()
```

4. Kotlin (TFLite Inference)

```
val tfliteModel = Interpreter(loadModelFile())

val input = preprocessImage(bitmap)

val result = Array(1) { FloatArray(39) }

tfliteModel.run(input, result
```