An Application for Crop Disease Diagnosis using Convolutional Neural Network

B. Tech. Project Report

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Abstract

In India two third of the population i.e approximately 70% relies on agriculture for their livelihood. Agriculture sector occupies about 20.5% of total GDP (Gross Domestic Product) in India. Crop Diseases cause yield loss up to 70% causing major problems for the farmers impacting their income. Potential reason behind this is farmers unable to identify disease on the crops. Traditionally, crop disease detection has been done through visual inspection by trained experts. These traditional methods include macroscopic and microscopic examination, serological tests, etc. But these methods require specific knowledge, skills, and equipment and can be time-consuming and labor-intensive.

With advancement in technology, there are new methods like machine learning and computer vision to detect the disease in crops which are faster and more efficient. In recent years there have been models like ANN (Artificial Neural Network), KNN (K-Nearest Neighbors) developed for crop disease detection. ANN requires a lot of computational resources to train and can be prone to overfitting. Whereas KNN can have difficulty in handling highly non-linear data as well as it can be computationally expensive while handling large datasets. The results of these models can be affected by presence of outliers and noise in the data. To overcome these flaws, we propose a model of ResNet (Residual Network) which uses CNN (Convolutional Neural Network). ResNet is a model that achieves higher accuracy compared to shallower models like ANN and KNN. It is able to handle large datasets using a residual learning strategy. Also ResNet is able to handle noise and outliers as well as overfitting by using skip connections and residual blocks. All these benefits make ResNet a more powerful model for crop disease detection especially when data is scarce, noisy and high dimensional.

Our aim is to develop an application using the model that we have implemented. This app will take leaf image as an input and it will predict crop disease based on that image. Our goal is to make our application more user-friendly so that it will be beneficial for farmers. Our application can help farmers to improve their crop yield, reduce crop loss and increase their profit.

Contents

List of Tables

List of Figures

List of Abbrevations

GDP Gross Domestic Product

ANN Artificial Neural Network

ResNet Residual Network

CNN Convolutional Neural Network

SVM Support Vector Machine

ReLU Rectified Linear activation Unit

Adam Adaptive Moment Estimation

Chapter 1

Introduction

Agriculture plays a crucial role in India, where two-thirds of the population, approximately 70%, rely on it for their livelihood [1]. The agriculture sector contributes approximately 20.5% to the total GDP of the country. However, crop diseases pose a major challenge for farmers, causing yield losses of up to 70% [1]. This has a significant impact on the income of farmers and is often a result of the inability to identify crop diseases. Traditionally, crop disease detection was performed through visual inspection by trained experts, using methods such as macroscopic and microscopic examination, serological tests, and others. These methods can be time-consuming and labor-intensive, requiring specific knowledge and skills, as well as specific equipment.

With advancements in technology, new methods for crop disease detection have emerged, including machine learning and computer vision. ANN and KNN are examples of models that have been developed for crop disease detection. However, ANN requires a lot of computational resources to train and is prone to overfitting [2][3]. KNN, on the other hand, can have difficulty handling highly non-linear data, and can also be computationally expensive when working with large datasets[4]. The results of these models can be affected by the presence of outliers and noise in the data, making it difficult to achieve high accuracy.

To overcome these limitations, we propose a ResNet model that uses CNN. ResNet is a more powerful model for crop disease detection compared to shallower models like ANN and KNN, as it is able to handle large datasets and overcome overfitting through residual learning and skip connections [1]. Additionally, it can handle noise and outliers effectively. Thus, ResNet is the preferred model for crop disease detection due to its high accuracy and ability to handle large datasets, noise and outliers, and to prevent overfitting.

Our goal is to develop an application that utilizes the ResNet model to detect crop diseases. The application will take leaf images as input and predict the disease based on that image. Our aim is to make the application user-friendly. This application will be of great benefit to farmers, as it will help them to improve their crop yields, reduce crop loss, and increase their profits. Additionally, the application could be used by agricultural organizations and government bodies to monitor crop health on a larger scale, providing insights into disease trends and helping to prevent widespread outbreaks. By leveraging technology, we can help to make agriculture more sustainable and secure, benefiting both farmers and the wider community.

Chapter 2

Literature Review

From our study we got to know that there have been several studies on the application of deep learning and machine learning techniques for crop disease detection. The studies have used different models such as EfficientNetV2 [5][6], YoloV5 [6], ResNet, VGG16 & VGG19 [7],VGGNET Transfer Learning[8], Random Forest [9], SVM [10][11][12], Decision tree[13], CNN [14][15], LeNet [16], k-NN [4], and ANN [2][3]. The batch size varies from 10 to 64 [16][7], and the accuracy of the models varies from 70.14% to 98.3% [9][3].

The advantages of the models include faster training time, and ability to work under challenging conditions. The disadvantages include the limitations of the models to predict disease in specific crops only, low accuracy, and high computational complexity. Also some models require use of hardware components. There have also been studies that used techniques like data augmentation, transfer learning, and fine-tuning to enhance the performance of the models.

Table 2.1: Literature Review

Year	Title	Model	Accuracy	Advantages	Disadvantages
2022	Application of EfficientNetV2 and YoloV5 for tomato leaf disease identification. [6]	EfficientNetV2 And YoloV5	95.35%	EfficientNetV2 model improve training accuracy whereas yoloV5 shorten the training time	Model can only detect tomato crop disease.
2021	Residual Neural Network (ResNet) Based Plant Leaf Disease Detection and Classification. [1]	ResNet	Classification - 85.38% Identification - 91.18%	Enhance performance of the neural network due to presence of more layers.	Model can only predict diseases on rose and cucumber plants.
2021	Cardamom Plant Disease Detection Approach Using EfficientNetV2. [5]	EfficientNetV2	94.10% (Cardamom Dataset)	U2 net architecture removes the complex background, which produces results without deteriorating the quality of the original image	Model can predict diseases of cardamom plants only.
2020	Potato Leaf Disease Classification Using Deep Learning Approach. [7]	VGG16 & VGG19	91%	Data augmentation process is added.	Model can classify only potato leaf disease. It is not generalised for other plants.
2020	Using deep transfer learning for image-based plant disease identification. [8]	VGGNET Transfer Learning	91.83%	Model uses batch normalization and Swish activation function	– The model was tested only on maize and rice dataset. – Size of dataset used is small (1000)
2019	Disease Detection and Classification in Agricultural Plants Using Convolutional Neural Networks. [15]	CNN (Convolutional Neural Networks)	88 %	Model requires less time for training.	It does not predict disease. It just classifies whether a plant is healthy or unhealthy.
2019	Rice Leaf Disease Detection Using Machine Learning Techniques. [13]	Decision Trees	97.01 %	Data augmentation process is added.	– Size of the dataset used is small. i.e., 480 images – Model can predict only rice leaf diseases.
2019	Deep Learning Based on NASNet for Plant Disease Recognition Using Leave Images. [14]	Convolutional Neural networks	93.82 %	The model was fine-tuned using techniques like differential learning rates, cyclical learning rates and test-time augmentation (TTA) to improve model accuracy without a reduction in training efficiency.	It does not predict disease. It just classifies whether a plant leaf is healthy or unhealthy.

Table 2.2: Literature Review Continued...

Year	Title	Model	Accuracy	Advantages	Disadvantages
2018	Plant Disease Detection Using Machine Learning. [9]	Random Forest	70.14 %	– Overcome the disadvantage of overfitting. – It handles both numerical and categorical data.	– Accuracy is less. – Size of the dataset used is small. (160 images). – It does not predict disease. It just classifies whether a plant is healthy or unhealthy
2017	Plant Disease Detection using Hyperspectral Imaging. [10]	Hyperspectral Imaging and SVM	93 %	Instead of relying on only one component it uses a full electromagnetic spectrum.	Hardware like hyperspectral imaging systems is required making the model expensive.
2017	Machine learning regression technique for cotton leaf disease detection and controlling using IoT. [11]	Support Vector Machine-Based Regression Technique	83.26 %	Farmers can automatically detect the disease and know the remedies to control that disease.	– Hardware is used. – Size of the dataset used is small. (900 images)
2017	A Deep Learning-based Approach for Banana Leaf Diseases Classification. [16]	LeNet	92.88 %	Model can work under challenging conditions like illumination, complex background.	Model targets only two diseases of the banana plant. It is not generalised for other plants.
2016	Monitoring and Controlling Rice Diseases Using Image Processing Techniques. [4]	k-NN (k-Nearest Neighbor classifier) & MDC (Minimum Distance Classifier)	87.02% & 89.23% respectively	– Simple Implementation – Learn complex models easily.	– High computational complexity. – Model can predict only rice leaf diseases.
2016	Cucumber Disease Detection Using Artificial Neural Network. [2]	Artificial Neural Network	80.45%	Works well for more than one crop of different types.	-- Feature Selection is difficult. – Model can predict cucumber diseases only.
2016	Detection and Classification of Diseases of Grape Plant Using Opposite Color Local Binary Pattern Feature and Machine Learning for Automated Decision Support System. [15]	Multiclass Support Vector Machine	96.60 %	Performs accurate classification.	– Dataset used is small. i.e., 450 images. – Model can classify diseases of grapes only.
2015	Leaf Disease Classification Using Artificial Neural Network. [3]	ANN (Artificial Neural Network)	98.3%	Model requires less time for training.	It does not predict disease. It just classifies whether a plant is healthy or unhealthy.

Chapter 3

Research Gaps and Problem Statement

3.1 Research Gap

Based on existing reports we found out that there is lack of a comprehensive and generalized model that can accurately detect and classify crop diseases across different types of crops using a large and diverse dataset. Most of the models listed in our study have limitations in terms of the crop types they can detect diseases for, the less size of the dataset used, or their ability to only classify crops as healthy or unhealthy without predicting specific diseases. A potential research focus could be on developing a more versatile and robust model that can be applied to various crop species and trained on a larger and more diverse dataset to improve accuracy and generalization.

3.2 Problem Statement

To explore and make a comprehensive and generalized model with the help of CNN that can effectively detect and classify diseases across a specific range of local crop species using large and diverse dataset.

Chapter 4

Proposed Methodology

4.1 Dataset

We used the publicly available PlantVillage dataset for our crop disease diagnosis model. The dataset was curated by S. P. Mohanty and it consists of 87,000 RGB images of healthy and unhealthy crop leaves with 38 different classes. However, to focus on our experimentation, we narrowed down our selection to a subset of dataset that includes 25 classes.

The selected 25 classes, which are detailed in Figure 4.1 covers a range of specific local crop species and diseases. These 25 classes were chosen carefully to cover a range of specific local crop species and diseases. By selecting a diverse set of classes, we aimed to ensure that our model would be trained and evaluated accurately on various types of crop diseases. In this way, the broad set of selected classes provides a robust dataset that is suitable for both training and evaluation of our model.

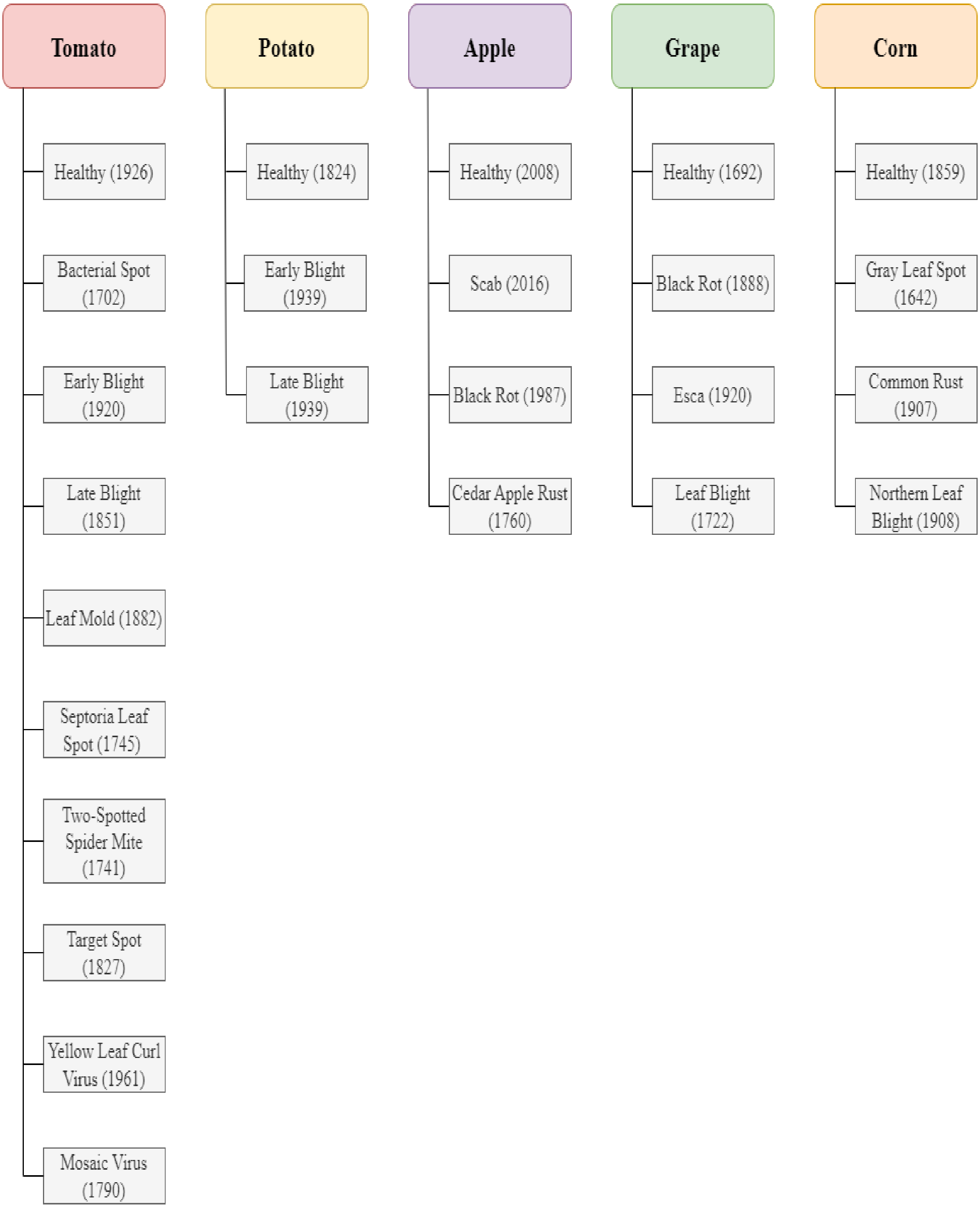
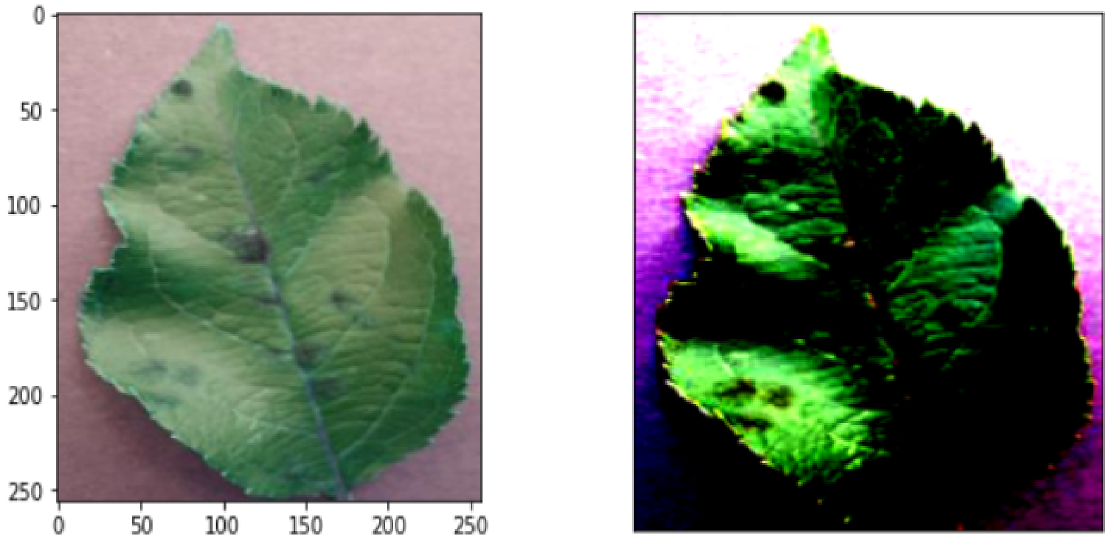


Figure 4.1: Dataset Overview

4.2 Data Analysis

4.2.1 Data Preprocessing

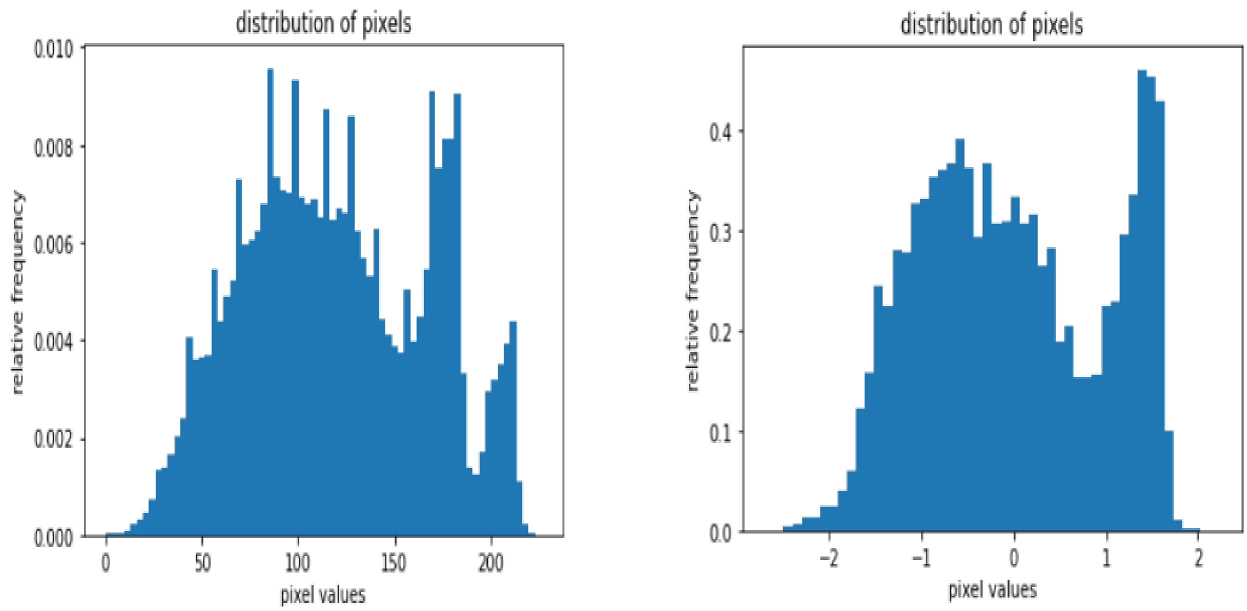
ResNet model requires preprocessed data because the input data needs to be in a specific format before it can be used by the model. This typically involves resizing, cropping, and normalizing the images. In crop disease diagnosis from leaf images using the ResNet model, preprocessing is especially important to achieve accurate results. Initially, the images are resized to a fixed size of 256 x 256 pixels to maintain consistency in the dataset. Then, the images are normalized to improve the performance of the model. After normalization, data augmentation techniques such as flipping, rotating, and cropping are applied to increase the size of the dataset and to introduce variation in the dataset. This helps in improving the performance of the model and prevents overfitting.



(a) Original Image

(b) Normalized Image

Figure 4.2: Apple Leaf



(a) Original Image (b) Normalized Image

Figure 4.3: Pixel Distribution

4.2.2 Hyperparameter Selection

Our solution incorporates the following optimization techniques that are well-suited for training deep neural networks, such as ResNet-based models to improve the accuracy of crop disease classification:

Optimizer

We use the Adam optimization algorithm to adjust the weights and learning rates of our neural network to minimize losses. By using the Adam optimizer, we are able to efficiently train our model to achieve high levels of accuracy in crop disease diagnosis.

Activation Function

Our solution employs the ReLU activation function, which efficiently prevents neuron activation and avoids gradient problems. By using the ReLU activation function, we are able to improve the performance of our model by preventing issues related to vanishing gradients, while also reducing the computational cost of training the model.

Loss Function

Our solution incorporates the cross-entropy loss function to measure the difference between predicted and expected outputs. The cross-entropy loss function is widely used for classification tasks and is particularly effective for multi-class classification, such as in our crop disease classification task. By using this loss function, we are able to effectively optimize our ResNet-based model to accurately classify crop leaf images.

By implementing these optimization techniques, we are able to achieve accurate and reliable reults of crop disease diagnosis using our ResNet-based approach.

4.2.3 Feature Extraction

The significance of feature extraction in ResNet is that it allows the model to learn more abstract features from the input images. By extracting high-level features, the model can better understand the content of the images and make more accurate predictions. This can be especially important for complex tasks where the image dataset is used. The preprocessed images are then fed into the ResNet model for feature extraction. The ResNet model is a deep learning model that can extract complex features from the images. The extracted features are then passed through a fully connected layer, which is used for classification.

4.3 ResNet

4.3.1 Basic Residual Block

ResNet addresses the problem of vanishing gradients in deep neural networks with a unique structure called a "residual block." A residual block contains two convolutional layers, a batch normalization layer, and a ReLU activation function. The output of the second convolutional layer is added to the input of the block, creating a shortcut connection that allows gradients to flow directly. The ResNet architecture is typically deep and contains multiple stages of residual blocks, followed by global average pooling, a fully connected layer, and softmax activation for classification. ResNet achieves state-of-the-art performance on image classification tasks.

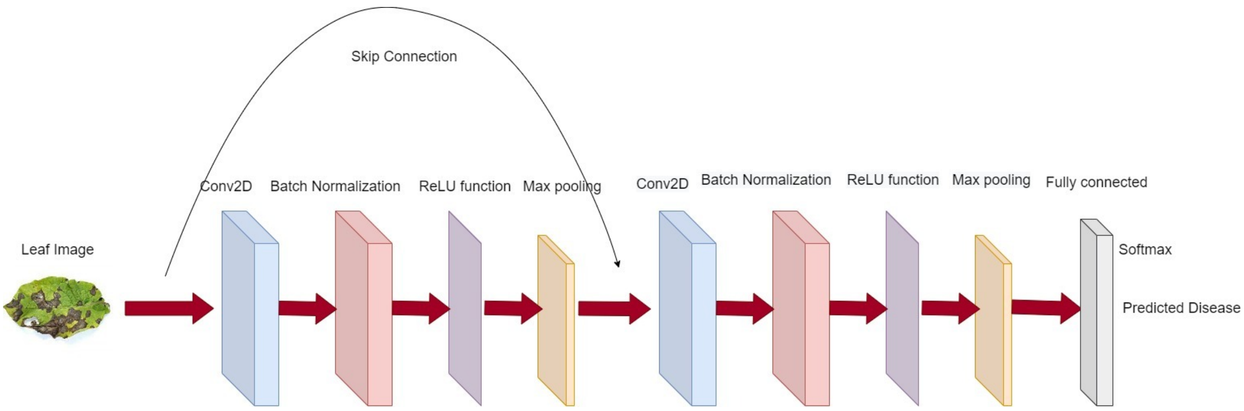


Figure 4.4: ResNet Block Diagram

4.3.2 ResNet9 Architecture

ResNet9 is a deep neural network architecture that is based on residual learning, a technique used to solve the problem of vanishing gradients in very deep neural networks.

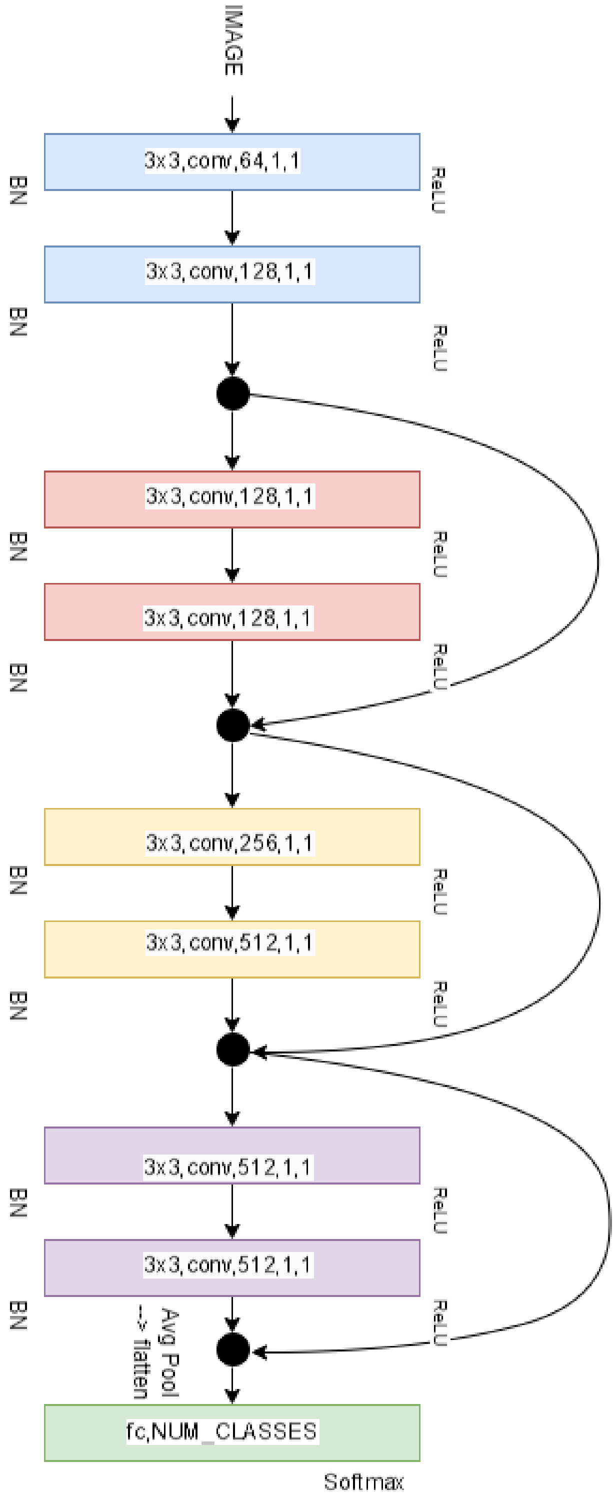


Figure 4.5: ResNet9 Architecture Diagram

The Residual Networks in the architecture consist of two or more residual blocks. Each residual block consists of two convolutional layers with batch normalization and ReLU activation functions, with a skip connection that bypasses these layers. The first convolutional layer has a 3x3 kernel size. The skip connection adds the input to the output of the second convolutional layer. The skip connection allows the network to learn residual mappings, which helps to alleviate the vanishing gradient problem and improve training performance. The output of each residual block is passed to the next residual block.

4.4 Project Plan

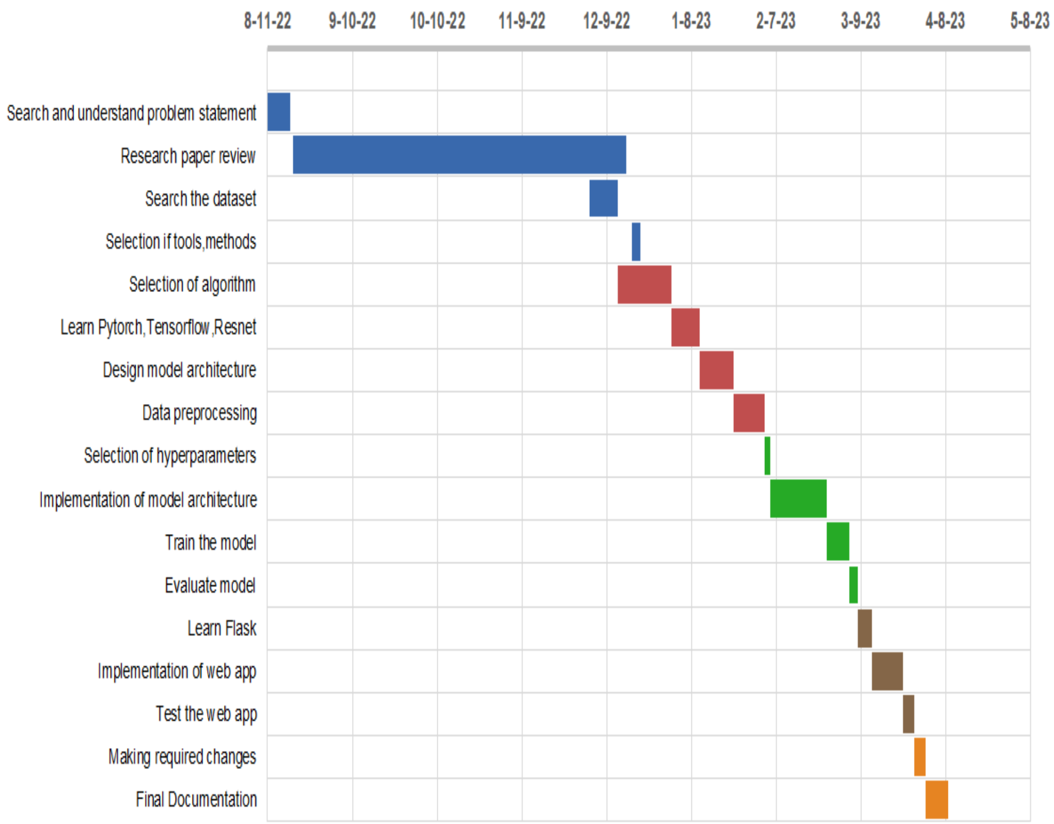


Figure 4.6: Project Plant Chart

Chapter 5

Experimental Setup

5.1 System Architechture

Architecture

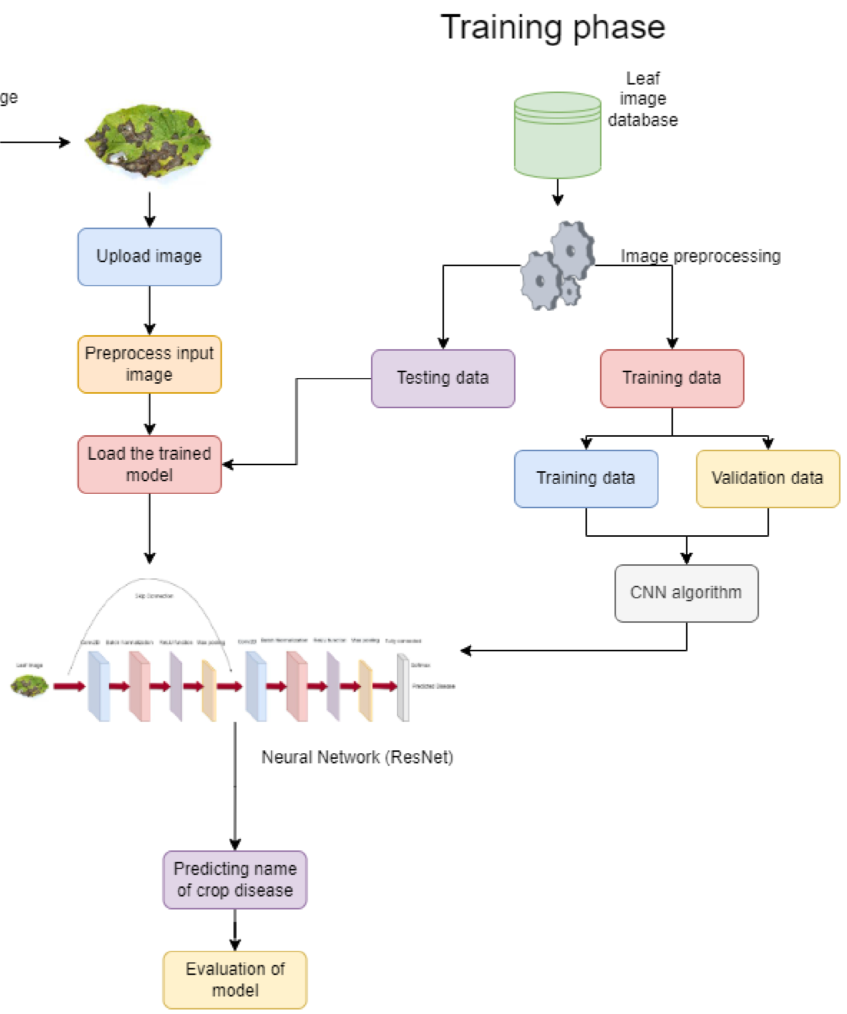


Figure 5.1: System Architechture

Usecase Diagram

In this usecase diagram, there are two actors - the user and the system. The user initiates the process by capturing an image of the leaf, which is then uploaded to the system. The system then preprocesses the input image and performs image segmentation to isolate the affected leaf. Next, the system detects the affected leaf and extracts its features. Based on the extracted features, the system classifies the disease and displays the name of the disease to the user.

In this system, the user is involved in the first two use cases - capturing and uploading the image. The remaining six use cases - preprocessing, segmentation, detection, feature extraction, disease classification, and displaying the name of the disease to the user are performed by the system.

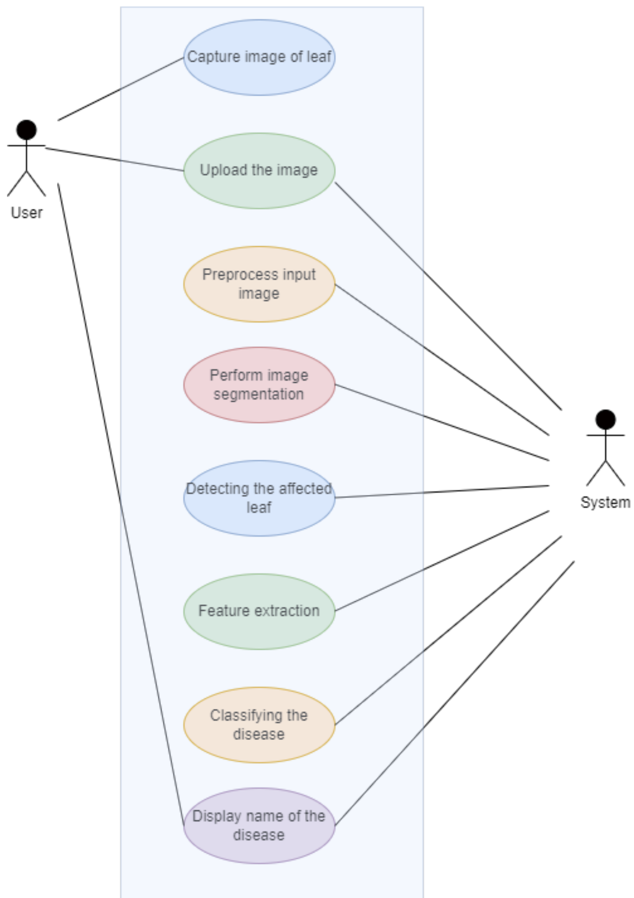


Figure 5.2: Usecase Diagram for the system

Sequence Diagram

In this sequence diagram, the user initiates the process by providing an input image to the system. The system then performs the methods of the system in sequence:
Preprocess the image → *Segment the image* → *Extract Feature* → *Train model*

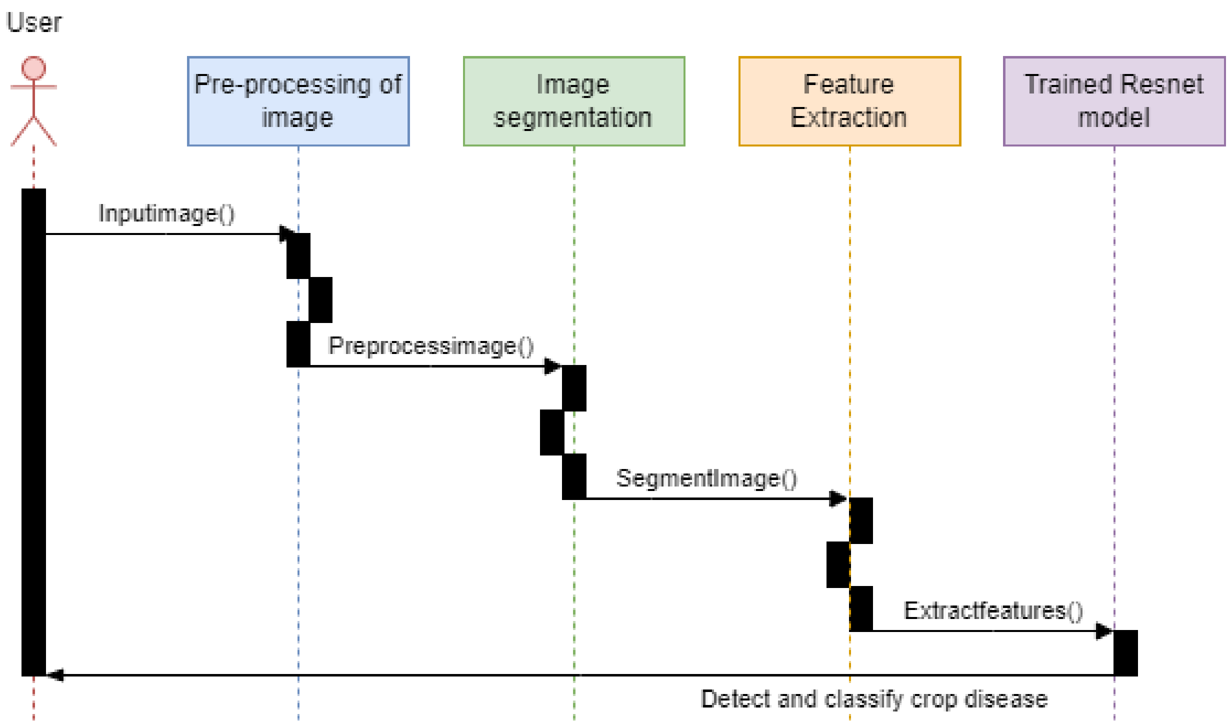


Figure 5.3: Sequence Diagram for the system

In Figure 5.3 it is shown that messages like Inputimage(), Preprocessimage(), SegmentImage() and Extractfeatures() are used to define communication between user and objects in the system.

5.2 System Requirement Specifications

5.2.1 Description

Product Perspective

The objective of this product is to develop a Crop Disease Diagnosis System that can discover and extract hidden information associated with crop diseases from a dataset. This system aims to exploit machine learning techniques, specifically the ResNet model, on agricultural data sets to assist in predicting crop diseases.

There are large volumes of records in the agricultural data domain, eventually making it necessary to use machine learning techniques to help in decision support and prediction in agriculture. Therefore, it contributes to business intelligence and helps farmers diagnose crop diseases early on.

Some specific objectives of the system are:

- Enable early detection of crop diseases to prevent widespread crop damage.
- Reduce the cost of labor and resources associated with manual detection methods.
- Help farmers save time and increase productivity.
- Improve the accuracy of crop disease diagnosis, leading to more effective treatment plans.

Product Function

1. Data collection: The dataset for this system is collected from Kaggle or other crop pathology databases. The dataset consist of images of healthy and diseased crop. The dataset can be augmented by rotating, flipping, and scaling the images to increase the variety of data.

2. Data cleaning: Data cleaning involves removing irrelevant or duplicate data, resizing images to a standard size, and converting the data to a format that can be used by the ResNet model. This step also involves splitting the dataset into training and testing sets to assess the performance of the model.

3. Model development: The ResNet model can be used for crop disease diagnosis by training the model on the cleaned dataset. The model can identify patterns and features in the images that are indicative of healthy or diseased crops. The model can be fine-tuned by adjusting the hyperparameters and adding more layers to improve the accuracy of the predictions.

4. Predictions: Once the model is trained, it can be used to predict whether a crop is healthy or diseased along with the disease name based on its image. The model can classify images with high accuracy, allowing for early detection of crop diseases and preventing further spread of the disease. This can help farmers and researchers identify crop diseases more accurately and efficiently, leading to better crop yields and healthier crops.

5.2.2 Operating Conditions

For a project on crop disease diagnosis using ResNet model, the following technocal requirements may be needed:

Software Requirements

- Operating System: Windows (10 and 11), Linux
- Programming Language: Python 3
- Platform: Google Colab
- Libraries: Python libraries such as `Numpy`, `pandas`, `pytorch`, `matplotlib`

Hardware Requirements

- Processor: 2.5+ GHz processor with a minimum of dual core.
- RAM: 8 GB minimum

5.2.3 Non-Functional Requirements

Reliability: For a crop disease diagnosis application using the ResNet model, it is important to have a reliable and strong structure. Changes made by the programmer should be reviewed. Bugs or errors discovered by users should be resolved promptly.

Maintenance: To ensure efficient performance of the application, the system monitoring and maintenance should be easy and straightforward. There should be no excess jobs running on different machines, and the application should be designed to make updates and maintenance easier.

Chapter 6

Results and Discussion

6.1 Performance Analysis

The figure 6.1 represents accuracy comparison between our ResNet9 model and VGG16 model [7].

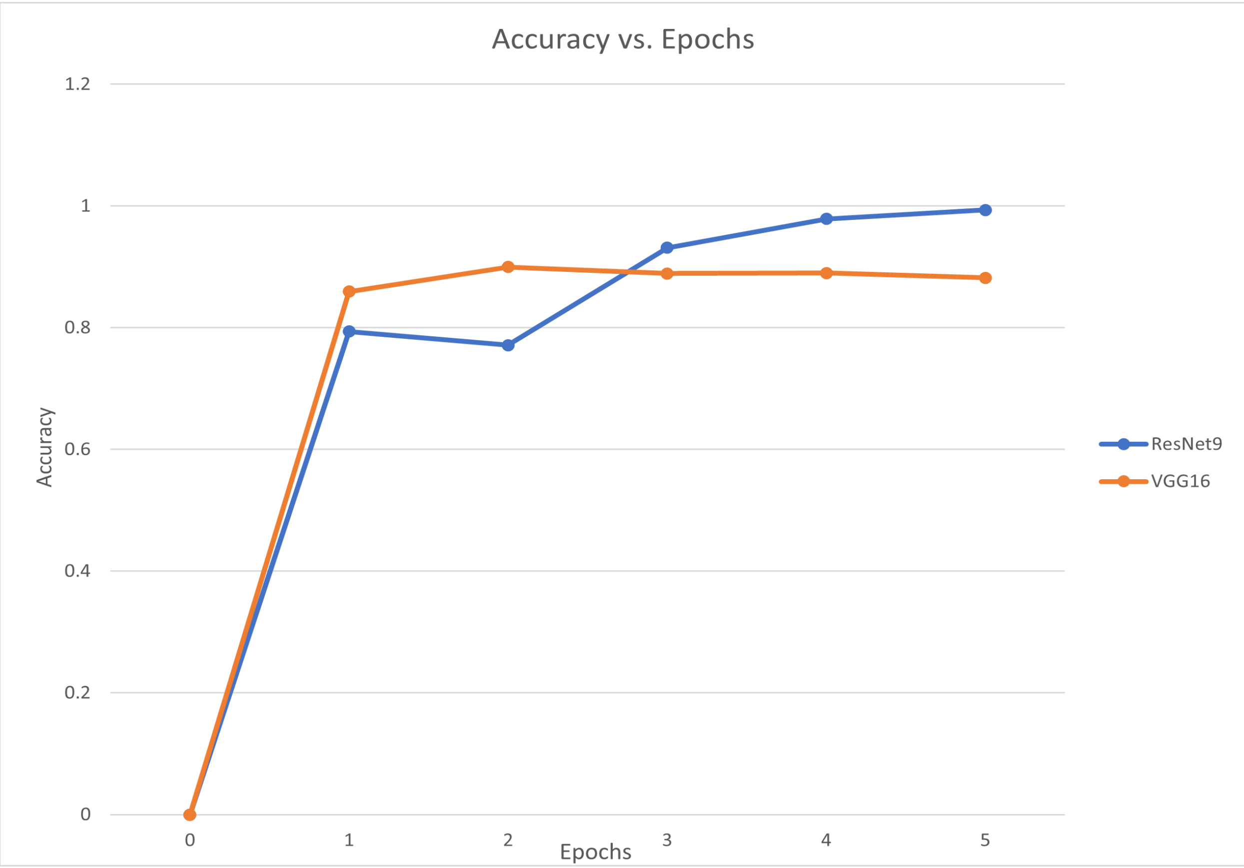


Figure 6.1: ResNet9 VS VGG16

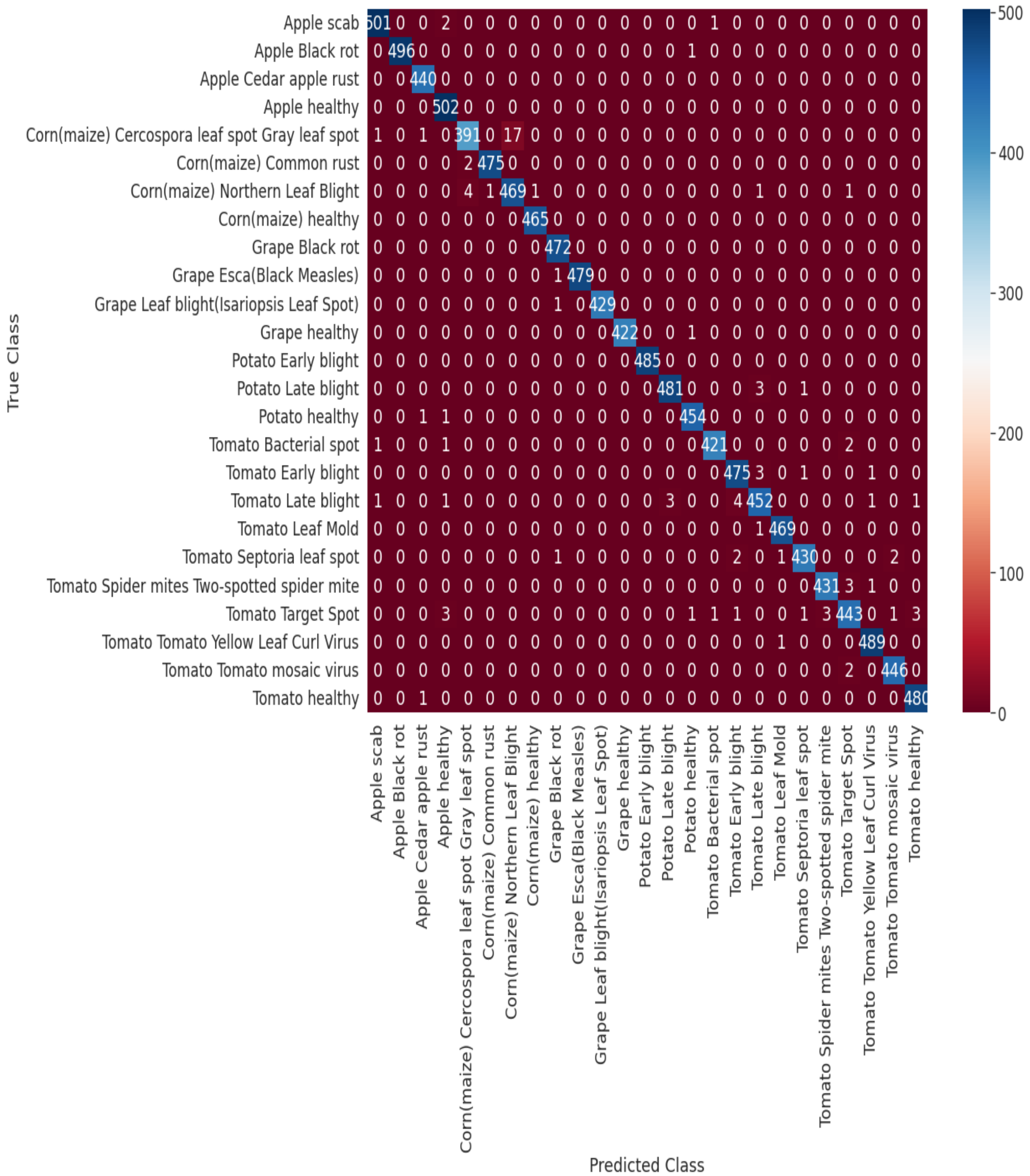
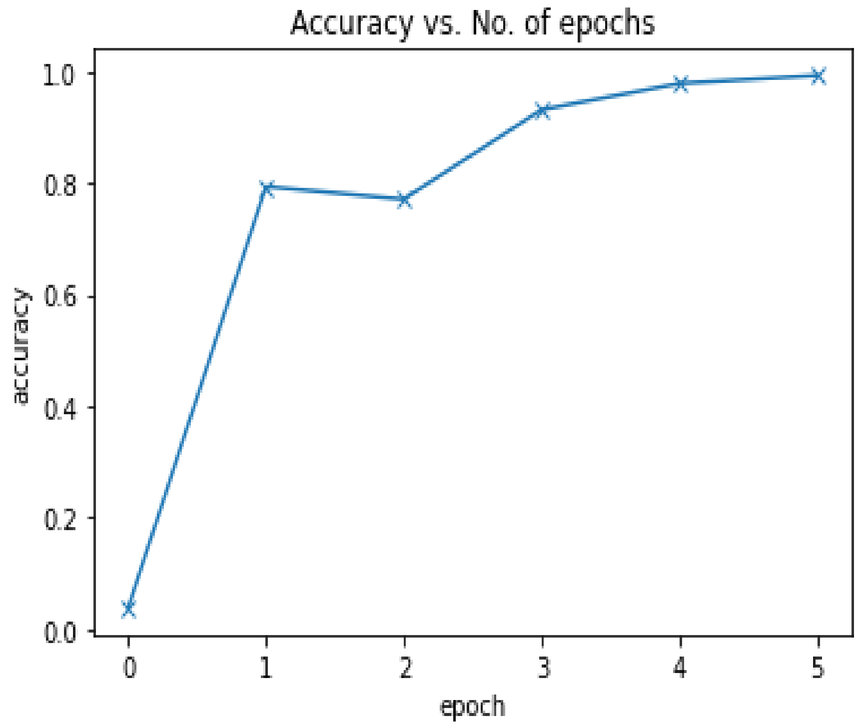
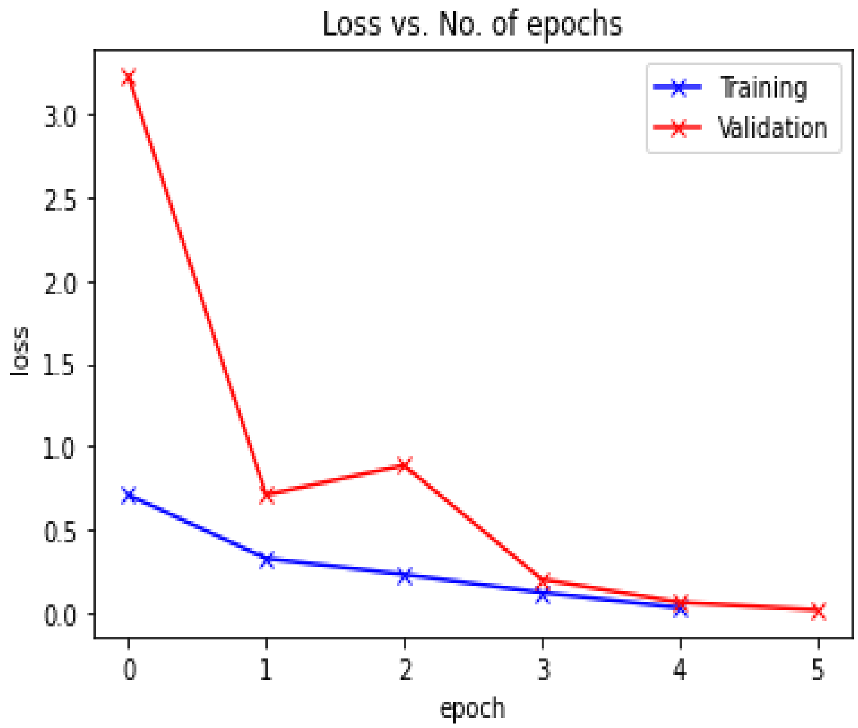


Figure 6.2: Heatmap

The following figure 6.3 shows the accuracy and loss graph against the number of epochs:



(a) Accuracy vs Epochs



(b) Loss Vs Epochs

Figure 6.3: Performance Analysis

6.2 WebApp Interface Design

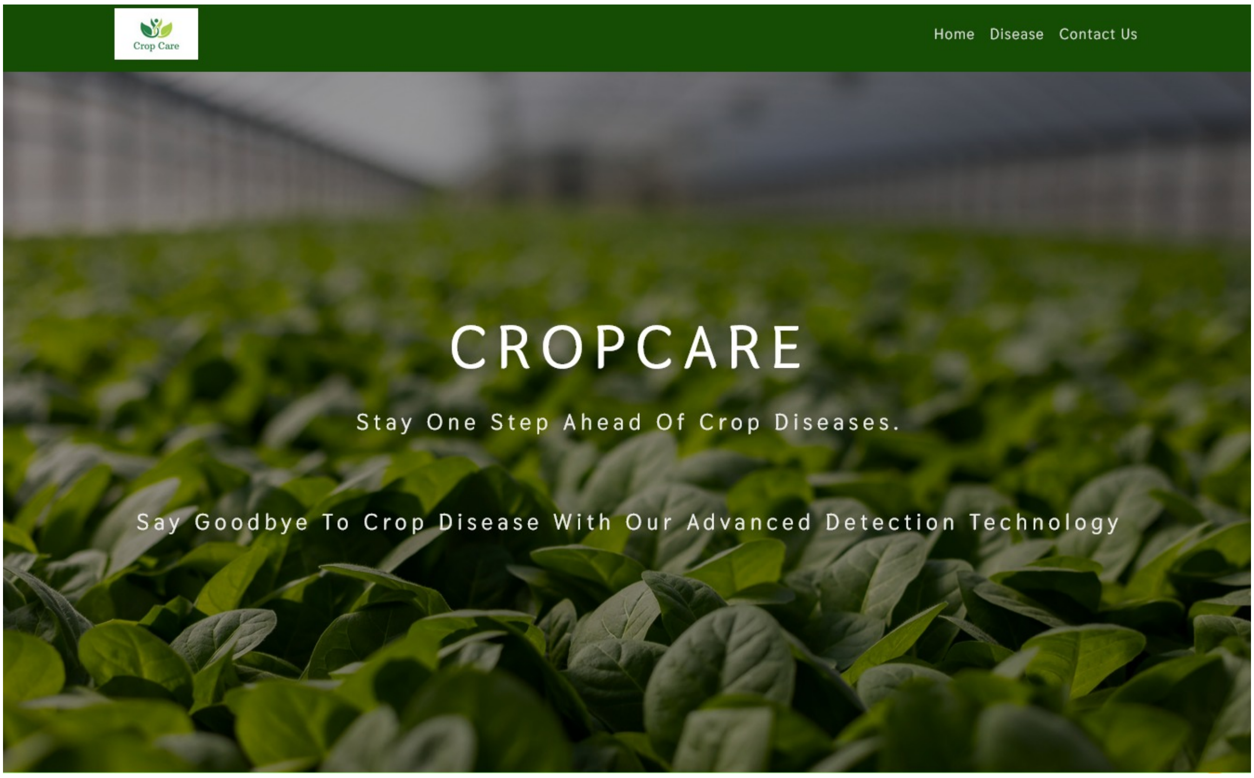


Figure 6.4: Homepage1

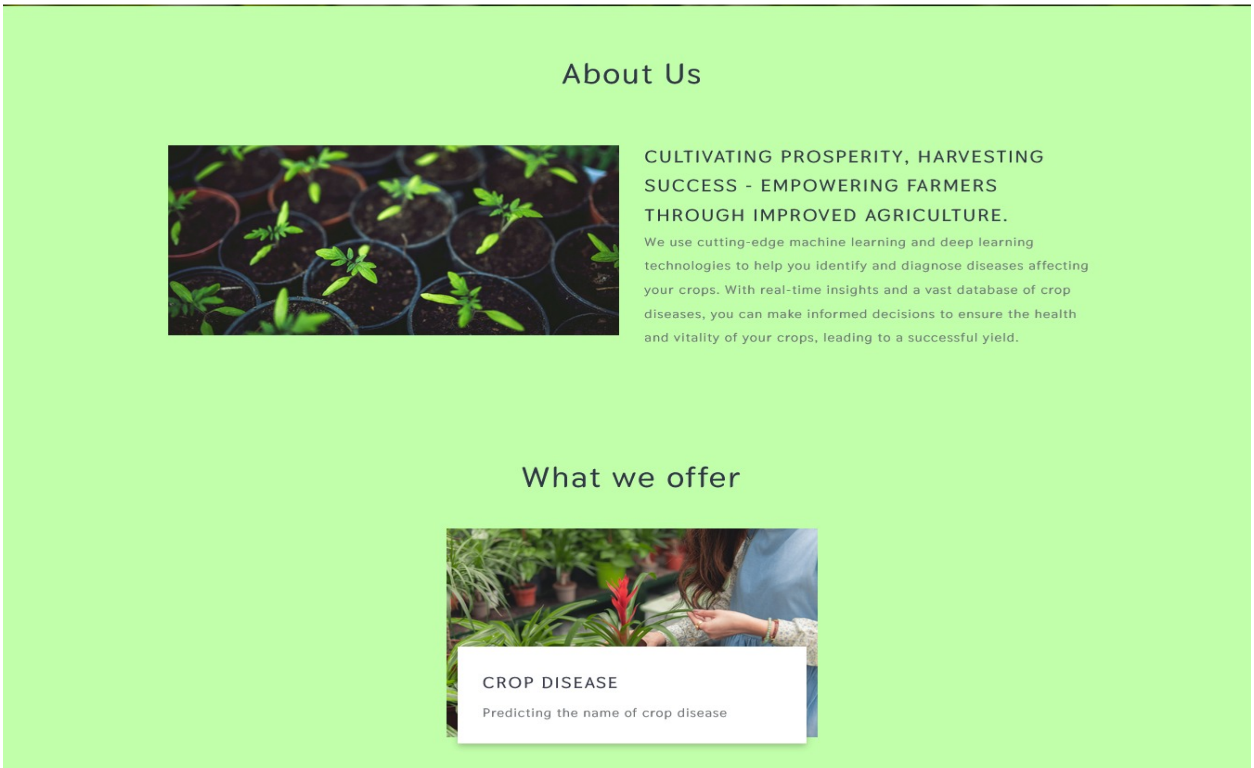
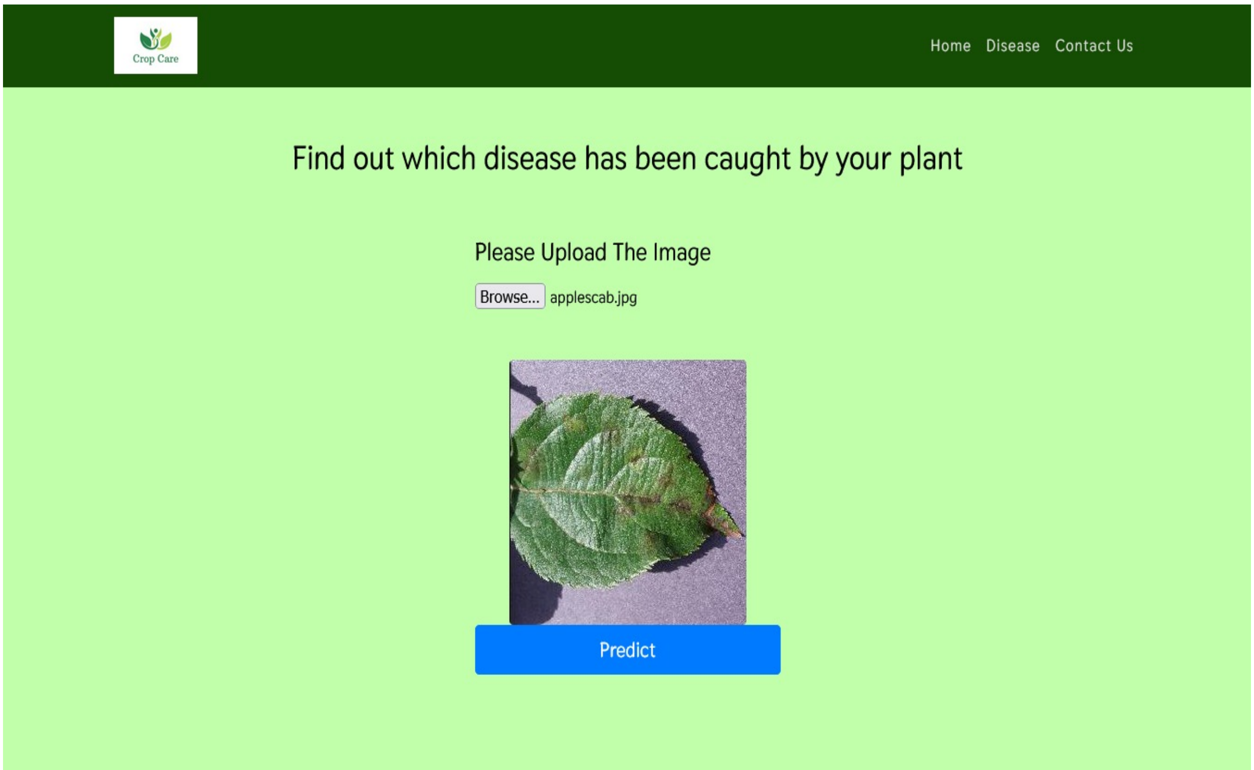
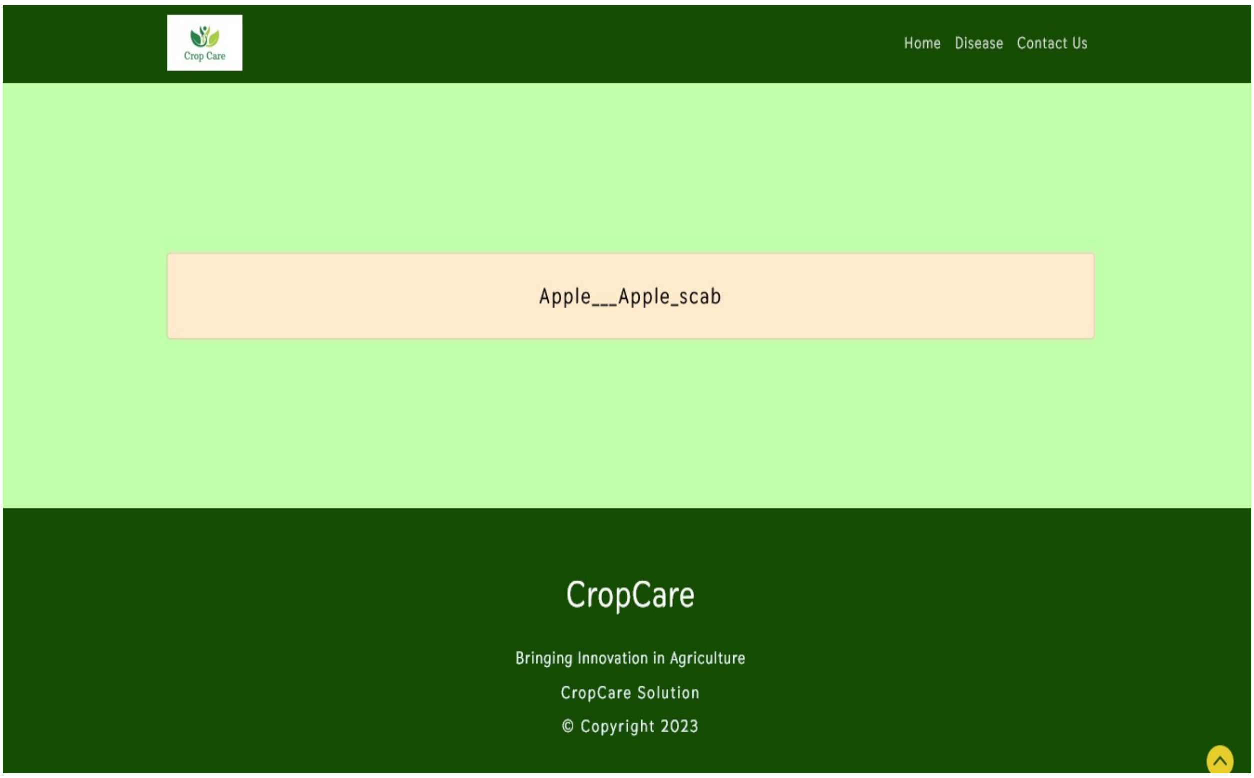


Figure 6.5: Homepage2

Figure 6.6: Homepage3



(a) Upload image



(b) Disease Prediction

Figure 6.7: Application Output

Chapter 7

Conclusion

This project provides valuable insights into the use of machine learning techniques for crop disease diagnosis. The classifier plays a critical role in the agriculture industry, enabling accurate and efficient prediction of crop diseases. Various machine learning techniques are studied and compared to identify the most effective systems. By improving the accuracy of crop disease prediction, these techniques can help farmers identify diseased crops in their early stages and implement preventive measures. The model's predictions can be used as a basis for developing measures to prevent crop disease. Similar models can be developed to study other crops and help farmers better serve their communities with analytical and classification techniques.

In the future, this project could be enhanced by integrating other computer vision and machine learning techniques to improve model accuracy and versatility. Additionally, the application could be scaled to include a larger database of crop diseases and to be made available to farmers in various regions in their regional languages to improve agriculture in those areas. By leveraging these techniques, more innovative solutions could be developed for farmers, leading to a more sustainable and profitable agriculture industry.

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