PLANT DISEASE DETECTION USING MACHINE LEARNING AND IMAGE PROCESSING

Project Report

Submitted to APJ Abdul Kalam Technological University in partial fulfillment of requirements for the award of degree

Bachelor of Technology

in

Computer Science and Engineering

by

MALATHI T	-	**STC20CS035**
MUHAMMED NAYIF M NAVAB METHA	-	**STC20CS038**
NOURIN S	-	**STC20CS043**
PRINCE SAJUVIN	-	**STC20CS044**

Guided by

Mr JAISON MATHEW JOHN
Assistant professor

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the Project Phase II Report titled **PLANT DISEASE DETECTION USING MACHINE LEARNING AND IMAGE PROCESSING** submitted by **MALATHI T**(STC20CS035), **MUHAMMED NAYIF M NAVAB METHA** (STC20CS038),**NOURIN S** (STC20CS043),**PRINCE SAJUVIN** (STC20CS044) to the APJ Abdul Kalam Technological University, Kerala in partialfulfillment of the B.Tech. Degree in Computer Science and Engineering is a bonafide record of the project phase I work carried out by them under our guidance and supervision.This report in any form has not been submitted to any other University or Institute for any purpose.

Guide

Mr JAISON MATHEW JOHN
Assistant professor
Dept of CSE

Supervisor

Mr JAISON MATHEW JOHN
Assistant professor
Dept of CSE

Head of Department

Dr. SHYJITH M .B
Dept of CSE

St.Thomas College of Engineering and Technology

Kozhuvalloor, Chengannur

INSTITUTION VISION

St. Thomas College of Engineering and Technology , Chengannur intends to be an institution of repute recognized for excellence in education ,innovation and social contribution.

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M2: **Life Long Learning**

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PEO3: Lifelong Learning

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PSO1: Professional Skills

Ability to understand the architecture and working of computer hardware and software.

PSO2: Design and Development Skills

Ability to design and develop software for technology application to fulfill industrial and social needs.

DECLARATION

We undersigned hereby declare that the project phase II report **PLANT DISEASE DETECTION USING MACHINE LEARNING AND IMAGE PROCESSING** submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala, is a Bonafide work done by us under the supervision of Mr JAISON MATHEW JOHN, Assistant Professor and Dr. SHYJITH M.B,Head of the Department, Department of Computer Science and Engineering, St Thomas College of Engineering and Technology. This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources. We also declare that we have adhered to ethics ofacademic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission hasnot been obtained. This report has not been previously formed the basis forth award of any degree, diploma or similar title of any other University.

02-05-2024

MALATHI T
MUHAMMED NAYIF M NAVAB METHA
NOURIN S
PRINCE SAJUVIN

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MALATHI T

MUHAMMED NAYIF M NAVAB METHA

NOURIN S

PRINCE SAJUVIN

ABSTRACT

Majority population of the world depends on agriculture as their primary occupation to earn their income. If any problems occur in that primary sector, it is going to affect the livelihood of the population adversely. Hence, it is necessary to maintain the proper balance in the agriculture sector by preventing the same from adverse effects like drought, plant diseases etc. In agriculture sector, especially horticulture yield more income to the farmers than other crops. These crops are prone to many diseases very easily and manual detection of disease in crops is very much difficult in the early stage.

To avoid errors due to manual detection of diseases, Machine learning methods are used. Image processing is done by capturing the infected region of image.

The infected image is provided for enhancement followed by image segmentation. then, the segmented image is given as input for the classification using convolutional neural network. Plant diseases pose significant threats to global food security by affecting crop yield and quality.

In recent years, the integration of image processing and machine learning techniques has emerged as a powerful approach for early and accurate detection of plant diseases. This paper provides a comprehensive review of the state-of-the-art methodologies employed in the field of plant disease detection using image processing and machine learning.

The first section of the review explores various image acquisition techniques, including traditional cameras, hyperspectral imaging, and drones equipped with advanced sensors. These technologies play a crucial role in capturing high-resolution and multispectral images that enable the detailed analysis of plant health.

This review synthesizes the recent advancements in plant disease detection through image processing and machine learning, emphasizing the integration of cutting-edge technologies to address challenges and improve the overall efficiency and reliability of plant health monitoring systems. The insights presented herein contribute to the ongoing efforts to develop sustainable and technology-driven solutions for global agriculture.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Plant disease detection using machine learning and image processing involves employing algorithms and techniques to identify, diagnose, and manage diseases affecting plants through the analysis of images. This process typically includes the following steps:

Image Acquisition: Capture images of plant leaves or parts showing symptoms of diseases using cameras or smartphones.

Preprocessing: Clean and enhance the images to improve their quality, remove noise, normalize lighting conditions, and enhance contrast for better analysis.

Feature Extraction: Extract relevant features from the images, such as color, texture, shape, and size, which are crucial in distinguishing between healthy and diseased plant parts.

Machine Learning Models: Utilize machine learning algorithms like Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), Random Forests, or others to classify and predict diseases based on the extracted features.

Training and Validation: Train the machine learning model using a dataset of labeled images (healthy and diseased plants) and validate its performance to ensure accuracy.

Testing and Prediction: Test the trained model on new, unseen images to predict and classify whether the plants are healthy or affected by diseases.

Deployment: Implement the developed model into an application or system that can assist farmers or agricultural experts in early disease detection and timely intervention to prevent crop damage.This approach aids farmers in adopting preventive measures, such as targeted pesticide or fungicide application or implementing suitable management practices, thereby minimizing yield loss and promoting sustainable agriculture.The integration of machine learning and image processing technologies offers a promising solution for efficient and accurate plant disease detection, contributing to better crop management and agricultural sustainability.

CHAPTER 2

LITERATURE SURVEY

2. 1 Overview of Literature Survey

SL NO:	Name of Journal	Dataset	Algorithm	Result
1.	Plant Disease Detection Using Image Processing	PlantVillage	RELIEF-F	86.5 % Accuracy
2.	Plant Disease Detection Using Machine Learning	PlantifyDr	Random Forests	70.14 % Accuracy
3.	Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning	Tomato Leaf Disease	Squeeze Net ,CNN	94 % Accuracy
4.	Plant Disease And Classification Using Image Processing Technuques: a review	Plant Disease Detection	K-nearest neighbor (KNN)	94% Accuracy
5.	An Approach for Mango Disease Recognition using K-Means Clustering and SVM classifier	MangoFruitDDS	Support machine	92% Accuracy
6.	Rice Disease Detection using Intensity Moments and Random Forest	RiceAI	Random Forest	91.47% Accuracy

Figure 1
Literature Survey

1. Plant Disease Detection Using Image Processing

Identification of the plant diseases is the key to preventing the losses in the yield and quantity of the agricultural product. The studies of the plant diseases mean the studies of visually observable patternsseen on the plant. Health monitoring and disease detection on plant is very critical for sustainable agriculture. It is very difficult to monitor the plant diseases manually. It requires tremendous amount of work, expertize in the plant diseases, and also require the excessive processing time. Hence, image processing is used for the detection of plant diseases. Disease detection involves the steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. This paper discussed the methods used for the detection of plant diseases using their leaves images. This paper also discussed some segmentation and feature extraction algorithm used in the plant disease detection.

The vegetation indices from hyper spectral data have been shown for indirect monitoring of plant diseases. But they cannot distinguish different diseases on crop. Wenjiang Huang et al developed the new spectral indices for identifying the winter wheat disease. They consider three different pests (Powdery mildew, yellow rust and aphids) in winter wheat for their study. The most and the least relevant wavelengths for different diseases were extracted using RELIEF-F algorithm. The classification accuracies of these new indices for healthy and infected leaves with powdery mildew, yellow rust and aphids were 86.5%, 85.2%, 91.6% and 93.5% respectively [1]. Enhanced images have high quality and clarity than the original image. Color images have primary colors red, green and blue. It is difficulapplications using RGB because of their range i.e. 0 to 255. Hence they convert the RGB images into the grey images. Then the histogram equalization which distributes the intensities of the images is applied on the image to enhance the plant disease images.

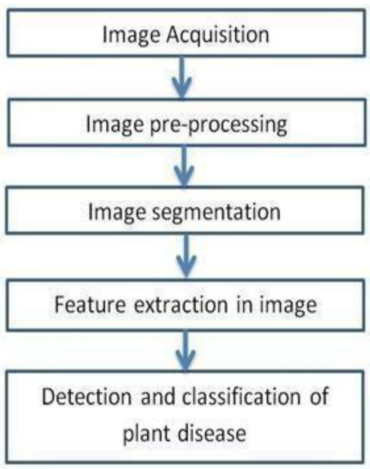


Figure 2

Flow chart

2. Plant Disease Detection Using Machine Learning:

Crop diseases are a noteworthy risk to sustenance security, however their quick distinguishing proof stays troublesome in numerous parts of the world because of the non attendance of the important foundation. Emergence of accurate techniques in the field of leaf-based image classification has shown impressive results. This paper makes use of Random Forest in identifying between healthy and diseased leaf from the data sets created. Our proposed paper includes various phases of implementation namely dataset creation,The agriculturist in provincial regions may think that it's hard to differentiate the malady which may be available in their harvests. It's not moderate for them to go to agribusiness office and discover what the infection may be. Our principle objective is to distinguish the illness introduce in a plant by watching its morphology by picture handling and machine learning.

Pests and Diseases results in the destruction of crops or part of the plant resulting in decreased food production leading to food insecurity. Also, knowledge about the pest management or control and diseases are less in various less developed countries. Toxic pathogens, poor disease control, drastic climate changes are one of the key factors which arises in dwindled food production.

Various modern technologies have emerged to minimize postharvest processing, to fortify agricultural sustainability and to maximize the productivity. Various Laboratory based approaches such as polymerase chain reaction, gas chromatography, mass spectrometry, thermography and hyper spectral techniques have been employed for disease identification. However, these techniques are not cost effective and are high time consuming.

In recent times, server based and mobile based approach for disease identification has been employed for disease identification. Several factors of these technologies being high resolution camera, high performance processing and extensive built in accessories are the added advantages resulting in automatic disease recognition.

Modern approaches such as machine learning and deep learning algorithm has been employed to increase the recognition rate and the accuracy of the results. Various researches have taken place under the field of machine learning for plant disease detection and diagnosis, such traditional machine learning approach being random forest, artificial neural network, support vector machine(SVM), fuzzy logic, K-means method, Convolutional neural networks etc.…

Random forests are as a whole, learning method for classification, regression and other tasks that operate by constructing a forest of the decision trees during the training time.

PROPOSED METHODOLOGY

To find out whether the leaf is diseased or healthy, certain steps must be followed. i.e., Preprocessing, Feature extraction, Training of classifier and Classification. Preprocessing of image, is bringing all the images size to a reduced uniform size. Then comes extracting features of a preprocessed image which is done with the help of HOG . HoG [6] is a feature descriptor used for object detection. In this feature descriptor the appearance of the object and the outline of the image is described by its intensity gradients. One of the advantage of HoG feature extraction is that it operates on the cells created. Any transformations doesn’t affect this.

Here we made use of three feature descriptors.

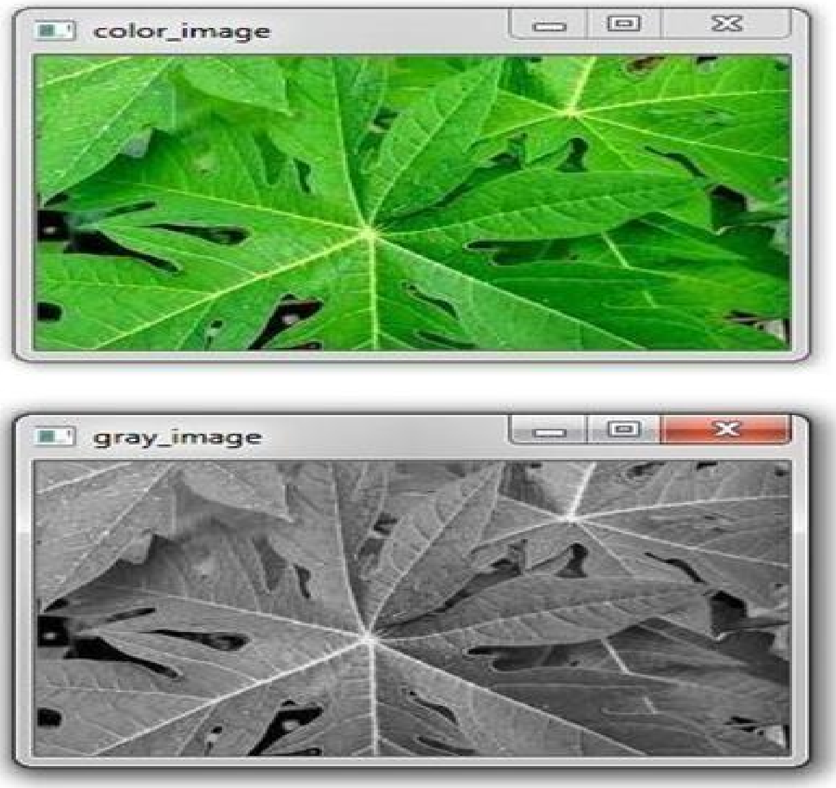


Figure 3

RGB to Gray scale conversion of a leaf.

Color Histogram: Color histogram gives the representation of the colors in the image. RGB is first converted to HSV color space and the histogram is calculated for the same. It is needed to convert the RGB image to HSV since HSV model aligns closely with how human eye discerns the colors in an image. Histogram plot [8] provides the description about the number of pixels available in the given color ranges

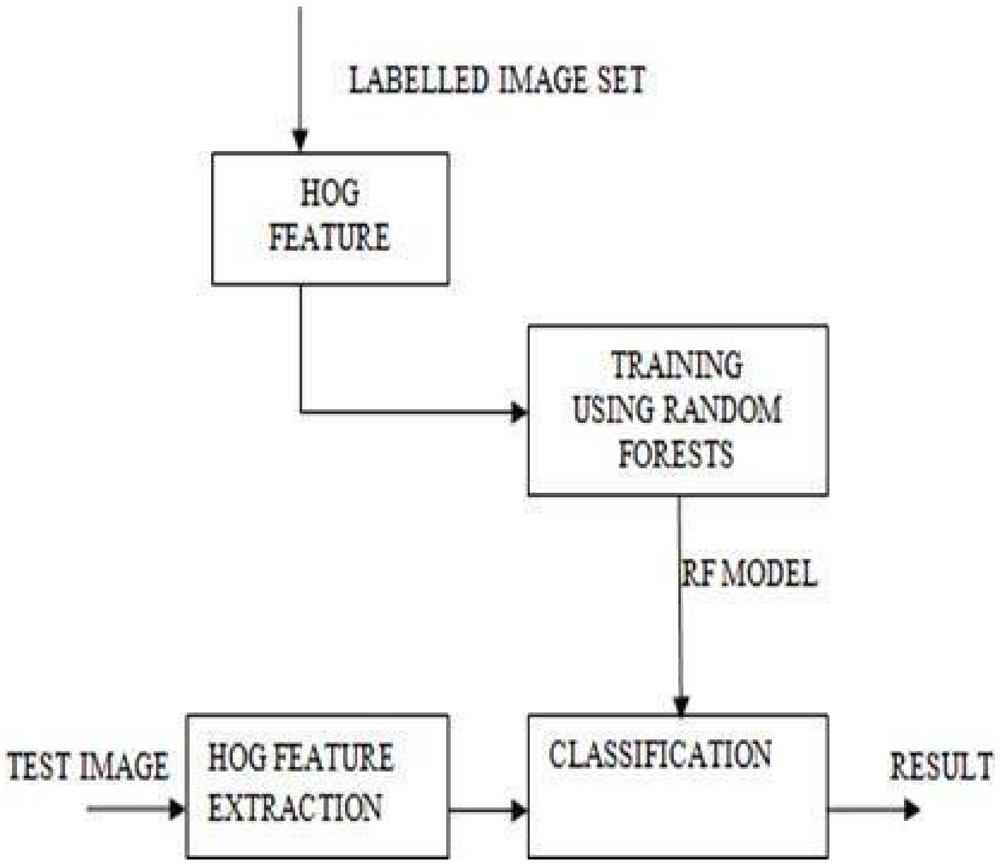


Figure 4

Architecture of the proposed model

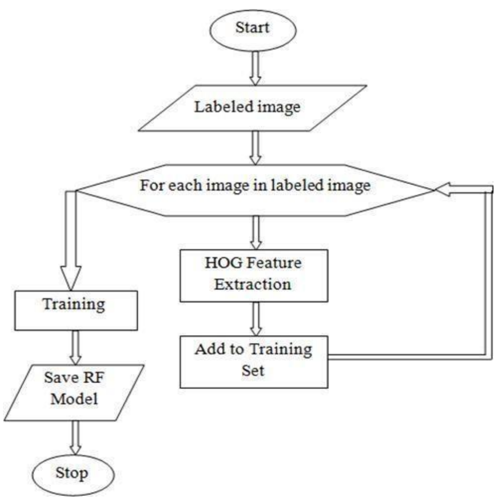


Figure.5
Flow chart for training

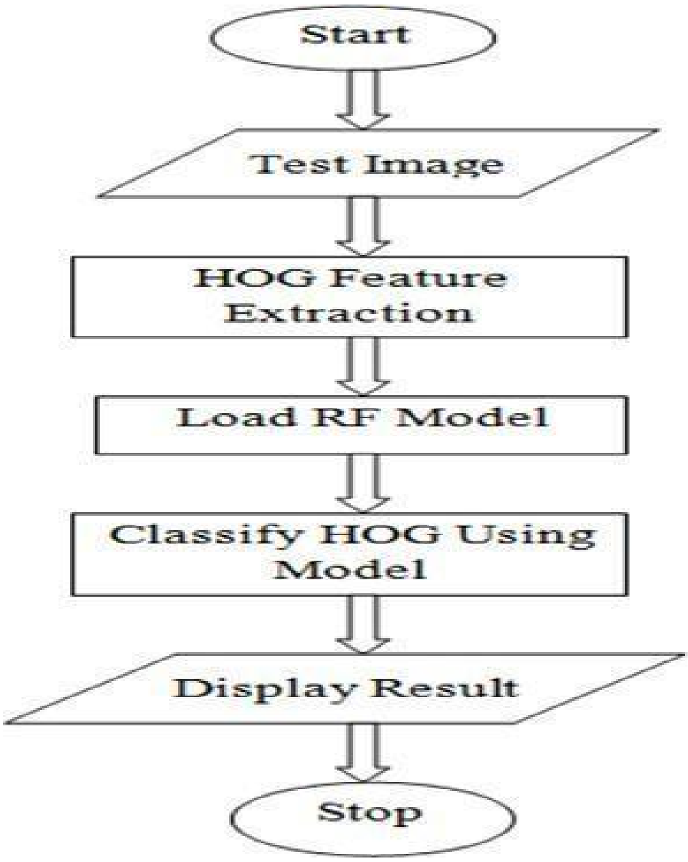


Figure 6
Flow chart for classification

The labeled datasets are segregated into training and testing data. The feature vector is generated for the training dataset using HoG feature extraction. The generated feature vector is trained under a Random forest classifier.As shown in the ‘Fig.5.” labeled training datasets are converted into their respective feature vectors by HoG feature extraction. These extracted feature vectors are saved under the training datasets. Further the trained feature vectors are trained under Random forest classifier.

As depicted in “Fig.6.” the feature vectors are extracted for the test image using HoG feature extraction. These generated feature vectors are given to the saved and trained classifier for predicting the results.

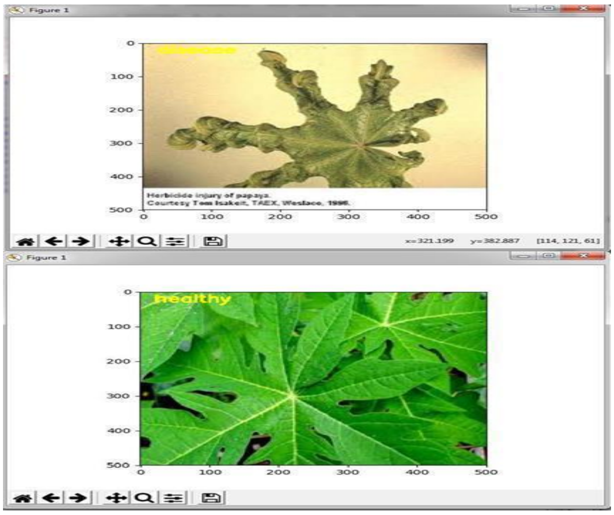


Figure 7
Images

First for any image we need to convert RGB image into gray scale image. This is done just because Hu moments shape descriptor and Haralick features can be calculated over single channel only. Therefore, it is necessary to convert RGB to gray scale before computing Hu moments and Haralick features.

To calculate histogram the image first must be converted to HSV (hue, saturation and value), so we are converting RGB image to an HSV image

3. Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning

The aim of this work is to detect diseases that occur on plants in tomato fields or in their greenhouses. For this purpose, deep learning was used to detect the various diseases on the leaves of tomato plants. In the study, it was aimed that the deep learning algorithm should be run in real time on the robot. So the robot will be able to detect the diseases of the plants while wandering manually or autonomously on the field orin the greenhouse. Likewise, diseases can also be detected from close-up photographs taken from plants by sensors built in fabricated greenhouses. The examined diseases in this study cause physical changes in the leaves of the tomato plant. These changes on the leaves can be seen with RGB cameras. In the previous studies, standard feature extraction methods on plant leaf images to detect diseases have been used. In this study, deep learning methods were used to detect diseases. Deep learning architecture selection was the key issue for the implementation. So that, two different deep learning network architectures were tested first AlexNet and then SqueezeNet. For bothof these deep learning networks training and validation were done on the Nvidia Jetson TX1. Tomato leaf images from the PlantVillage dataset has been used for the training. Ten different classes including healthy images are used. Trained networks are also tested on the images from the internet.

Tomato is one of the most produced crop all around the world. According to the statistics obtained fromthe Food and Agriculture Organization of the United Nations, approximately 170.750 kilotons of tomato produced in the year 2014 in all around the world [1]. According to Turkish Statistical Institute, Turkey has produced 12.600 kilotons of tomato in the year 2016 [2]. These production quantities are affected by the pests and diseases that occur in tomato plants. To prevent these diseases and pests, costly methods and various pesticides are used in the agriculture. The widespread use of these chemical methods harms plant health and human healthas well as affects the environment negatively. Also these methods, increases the production costs.

The diseases and pests effects the leaflets and leaves, the roots, the stems, and the fruits of the tomato plants [3]. Phonological changes on the leaves and leaflets on the tomato plants can be abnormal growth, discoloration, spots, damages, wilting desiccation, and necrosis [3]. In this study, diseases and pests affecting leaves and leaflets were examined. Since the Plantvillage [4] dataset is used in this work, only diseases

METHOD

It is defined the deep learning is a representation learning method at their survey [12]. Here representation learning means that algorithm finds the best way to represent data. Algorithm finds this representation through optimizations instead of semantic features. With this learning procedure, there is no need to do feature engineering. Because features are automatically extracted.

Mathematically, deep learning is artificial neural network with hidden layers. At the Fig. 1a, fully connected neural network with two hidden layers is shown and at the Fig. 1b, schematic representation of perceptron is shown. Perceptrons are inspired from the living neuron cells. Each perceptron has multiple inputs (at the Fig. 1b, only 5 inputs are shown) and activation function. Mathematical formulation of the neuron is given at the

(1). Activation function makes the answer of the neuron non-linear without activation functions network is onlylinear combinations of the inputs. There are a lot of activation functions in the literature such as sigmoid, tanh, ReLU. ReLU is one of the most used activation function and it is found quicker to train [9].

$= f(x1w1 + x2w2 + x3w3 + x4w4 + 5w5)$ each circle is a perceptron. At the beginning stage of the training weights of each perceptron is initialized. Initialization can be sampled from Gaussian with bias. In every

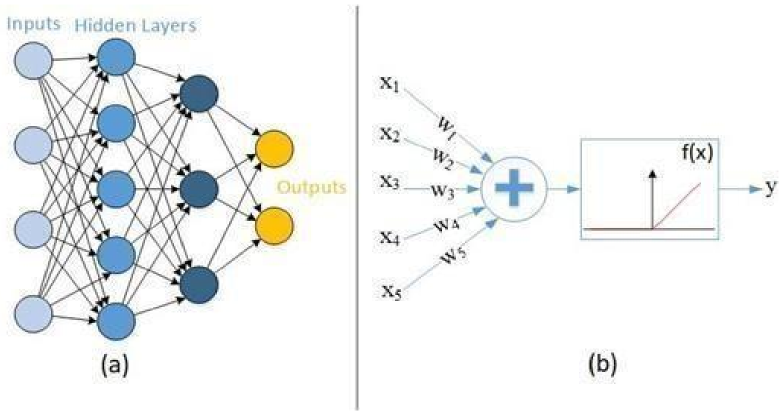


Figure 8

a) Deep neural network, b) Schematic representation of a perceptron.

Iteration step, all training data passes through the network. Since it is supervised learning, loss is calculated between ground truth and output of the network. Loss is the input of the optimization algorithm. Optimization algorithm updates the weights according to this loss. One of the most used optimization algorithm is Stochastic Gradient Descent (SGD) algorithm. Briefly, SGD minimizes the loss through iterations by updating means according to gradient.

4. Plant Disease Detection And Classification Using Image Processing Techniques: a review

These days, Computerized imaging innovation needs in the farming field. It can help agriculturists to create early discovery and classification of leaf plant disease. In the agribusiness field, there are a few sorts of the infection that can attack and appear through the leaf. In case the disease isn't identified early, it can be provide afew influences to the sum and quality of the generation. Leaf plant disease can be identified and classified utilizing advanced image processing. Leaves of the plant are utilized to decide the type of diseases that contaminates the crops. Agriculturists can make early choices which are they can analyze the leaf plant infection. Advanced Image processing could be a quick technique, consistent and more exact procedure for leaf plant malady discovery. In this paper, we review leaf plant disease detection and classification using image processing methods from different authors that help agriculturists in the agriculture field. It contains a few stages such as image acquisition, image processing, segmentation, feature extraction, and classification. Through early detection using the image processing technique, leaves of the plant are used to detect and classify the leaf plant disease. Some diseases that affect plants with the possible can cause overwhelming financial, social and ecological losses Early diagnosing disease by digital image processing is very important in accurate and timely (A. & L. N., 2017). This is can help agriculturists analyze the type of disease and can make early decisions on it. This review, discuss several types of image processing technique for disease detection on the plant. Unit one gives an introduction to leaf disease detection. Unit two clarifies the steps of image processing, followed by Unit three where gives a brief literature survey, which consists of all techniques used by all authors. In Unit four presents a review table for quick information about techniques used and results by all authors for different papers and ends with section 5 provides conclusionsfor this paper.

In the agriculture field,watching wellbeing and disease on crops is exceptionally imperativeto the effective development of crops on the cultivate. This requires extraordinary processing time and a parcel of works. The picture handling strategy can be utilized on leaf plant illness location. The pre-processing image will upgrade the image quality. Analysis of image processing will deliver great result. It incorporates color space change, picture enhancement, and picture segmentation. Mostly, the infection side effects can be seen on the leaves, stem, andfruits. The leaf of the plant can appear the indication infection. Image processing is the improvement of the picture that's handling an picture so that the comes about are more fitting for a specific application. Pre- Processing an image implies sharpening or de-blurring an out of center picture, highlighting edges.

5. An Approach for Mango Disease Recognition using K-Means Clustering and SVMClassifier.

Bangladesh extensively depends on agriculture in terms of economy as well as food security for its huge population. For this reason, it is very important to efficiently grow a plant and enhance its yield. We often face some problem which need to be solved. We build a Mango Disease Recognition system which can recognize the mango disease. It's Very useful to the farmers because using this system they can easily identify their mango disease which is very important to produce more fruits. Using our system user can easily identify the problem and they can take action for better production. There also some existing project of similar topic but theses project are not available to the all users. More over some system recognize disease very poorly and there have less accuracy and it's a huge problem to use the system. Comparing other system our system can be use more efficiently. Recognition of Mango diseases poses two challenging problems, i.e. detection and classification of disease. In here we used K means clustering for feature extraction and SVM for classification. The novelty of our work is that here we recognize the mango diseases which is not existing and our project accuracy is 94.13%. So we think user will be benefited from our project to produce more product which can effect in our economy.Fruits are the mainly significant agricultural food stuffs. Wide range of diversity faced by farmer to choice proper Fruit. As we know that Bangladesh is an agriculture oriented country that's why we are proposed to developed a project which can help our farmer to increase the productivity and food quality of their fruits at reduce expenditure and profit. Lots of fruits are grow in Bangladesh. Among them we work For Mango Disease Recognition. In our economic growth

Author (year) [ref]	Description	Accomplishment
Our work	Here we recognize the Mango disease using 250 image as training image and 12 image as a features set image. Here we also used k-means clustering to segment and SVM is used to classify.	Our accuracy level is 94.13% which is enough good than others.
Chopaade and Bhagyashri (2016) [3]	Their research process was only for disease detection without feature set and classification. That why it's a negligible work. They have not follow machine vision based technique.	There is no accuracy, they have only identifiable through histogram based thresholding segmentation algorithm process
Samajpati and Degadwala (2016) [4]	They follow a technique to recognize apple fruit. It works only for recognize disease using the random forest classifier. Here 70 sample image is used to training and testing purpose used 10 features image including features set 13.	They used k means clustering to segment the image having accuracy 60%-100%.
Rozario et al. (2016) [5]	They raised a method using image processing to only for detection of apple, banana, potato and tomato fruit. They are not work for classification and recognition the disease.	There is no accuracy here.
Kumar and Suhas (2016) [6]	They are proposed a model to recognition the fruit only using 243 image but there is no mentioned featured set. Its mean that there is missing the information.	All though there is missing the information their accuracy level was 87.47%
M.T. Habib et al. (2018) [7]	They offer a machine vision based pathway to recognize a papaya disease recognition both for fruit & leaf using k means cluster method. Where they used 10 feature set among 126 training image to classify the classifier using SVM.	Their accuracy was approximately 90%.
Kumiawati et al. (2009) [8]	They are attempt to implement an approach for recognition system for paddy leaf. They applied rule based classifier to classify 5 feature set out of 94 training image.	There was a better result than the others which are implemented by various researcher. Because they have 94.7% accuracy level.

Figure 9

Table

This project is implemented to reduce the waste of time and save money that would be helpful for general people. In our proposed work we show an approach to recognize the mango disease that follow in agro sector field. Here we used 2 features set according to 12 features from overall mango diseases recognition. Here we also used support Vector Machine(SVM) to extract feature. Based on the feature we are success to achieve the expected result with classifier. Through all of the analysis we can says that our system will work properly. We obtained accuracy 95% that is good enough to identifydisease accurately. So we think our project will be helpful to contribute our economy. In future there will be a bright future to implement it for a large amount of dataset and also can implement it android phone as well as smart phone to recognize a variety of Mango disease.

6. Rice Disease Detection using Intensity Moments and Random Forest:

Rice is the most significant n o u rishment h a r vests o n the planet, especially in Bangladesh. In Bangladesh farmers usu- ally go through with lots of problems in their rice plant. Un- perceived infections of paddy can prompt significant h a r m to harvest development and eventually diminished the creation of yields. Various sicknesses influence t he g rowth o f p addy, three primary diseases that usually happen in the plant: Bacterial Leaf Blight of rice, Blast, and Brown spot of rice. Blight, Blast, and Brown spot diseases consisting of some similar characteristics. Someone can easily be perplexed by viewing all these same features of plant diseases. Above all crops can be influenced by sickness at several phases. some plant diseases is not an easy task to find b y t he farmers. They are not attentive to suitable controlling to cure their rice disease. If farmers can identify conditions of diseases smoothly at the primary stage it will be so helpful for them. By this identification, farmers can save staple food, rice. Without rice many people cannot stay on a single day. Most of the countries economy is mostly dependenton rice as well. So saving rice from various diseases isvery helpful for both life and the economy For this reason, an appreciative leaf disease recognition pro- cess of rice is a super necessary task for both life and economy. In the work of recognizing the leaf image, different schemes already can identify diseases nicely. Few undertakings are obligatory in the first step of recognizing the paddy leaf disease. This system is involved with the recognizable proof of the rice leaf diseases, which is consists of pre-processing of the image, converting the RGB images into gray images. Then intensity moments extraction, and lastly classification of the leaf diseases. Different categories of image formats like JPEG, JPG, PNG, GIF, BMP, etc. farmers can have when they capture images from the paddy field. So the collection of various kinds of rice leaf disease images is the first task. Color processing is supposed the most significant work in image preparation and significant perception for identifying various classes. In the pre-processing step of an image, resizing the image, remove noise, or segmentation those calculation is essential often. Texture features, structure features, and geometric features are usually well known to all. Rice leaf image represents one or more features. Normally for feature extraction feature vector is created using Mean, Standard Deviation, Variance, Midrange, IQR, and Median. The classification technique is propounding for recognizing whether theimages are affected by diseases or not. Various rice leaf diseases can purposive by some classifiers like SVM, Random Forest, and Euclidean distance using KNN. Machine learning and image processing technique ca

CHAPTER 3
EXISTING SYSTEM

I. INTRODUCTION

obligatory in the first step of recognizing the paddy leaf disease. This system is involved with the recognizable proof of the rice leaf diseases, which is consists of pre-processing of the image, converting the RGB images into gray images. Then intensity moments extraction, and lastly classification of the leaf diseases. Different categories of image formats like JPEG, JPG, PNG, GIF, BMP, etc. farmers can have when they capture images from the paddy field. So the collection of various kinds of rice leaf disease images is the first task. Color processing is supposed the most significant work in image preparation and significant perception for identifying various classes. In the pre-processing step of an image, resizing the image, remove noise, or segmentation those calculation is essential often. Texture feausually well known to all. Rice leaf image represents one or more features.

Normally for feature extraction feature vector is created using MeRice is the most significant nourishment harvests o n the propounding for recognizing whether the images are affected planet, especially in Bangladesh. In Bangladesh farmers usu- ally go through with lots of problems in their rice plant. Un-perceived infections of paddy can prompt significant harm to harvest development and eventually diminished the creation of yields.

Various sicknesses influence t he g rowth o f p addy, three primary diseases that usually happen in the plant: Bacterial Leaf Blight of rice, Blast, and Brown spot of rice. Blight, Blast, and Brown spot diseases consisting of some similar characteristics. Someone can easily be perplexed by viewing all these same features of plant diseases

II. PROPOSED METHOD

This system is for diagnosing rice leaf disease contains some processes like - first acquisition of the image of rice leaf, pre- process the image, extracting features from those images, and classification of the image according to disease name. Datasets are split-up into two sets. Two-third of data from the dataset i.e. total of 352 images (276 original images and the remaining are augmented from) are avail of training.

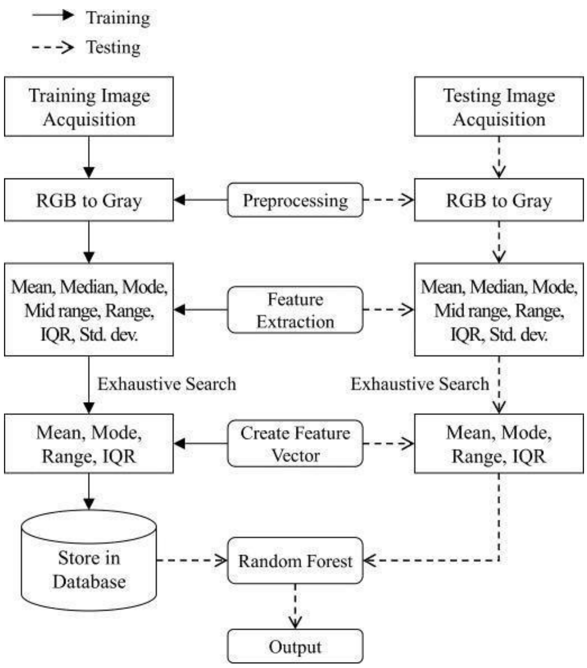


Figure. 10
Proposed architecture of rice leaf disease detection.

One-third of images (i.e. 176 images) from the rice leaf dataset attained for testing the disease. Though intensity mo- ments are not novel, their usage is not well explored. In this system, we experimented with various intensity moments as a feature vector to figure out the best combination for detecting rice disease for this very specific dataset.

A. Training Phase

Image Accusation: The dataset contains three types of rice leaf diseases (Blast, Blight, and Brown spot) images are used in the work. The provided dataset is of optimum age of 3 to 4 weeks. The reason behind it is leaf which is too old or too young isn't suitable for detecting diseases perfectly. In fig 2 some sample of rice leaf disease is shown. Image Pre-processing: Displaying larger images sometimes makes the problem in storage. So resizing this image into 300*300 pixels and converting the RGB image into a grayscale image is required.Feature Extraction: When the input data containing ample records with a large input data size then data can modify into a set of features for better calculation . There are several methods to extract color features fromimages. The color moment is an effective and easy color feature functioning process. Its math foundation lies that any color distribution can show with its moment . Here for feature extraction intensity moment is under consideration for getting results in an effective and meaningful way.

(a) Blast (b) Blight (c) Brown spot

(d) Blast (e) Blight (f) Brown spot

Figure 11: Some sample images from the dataset

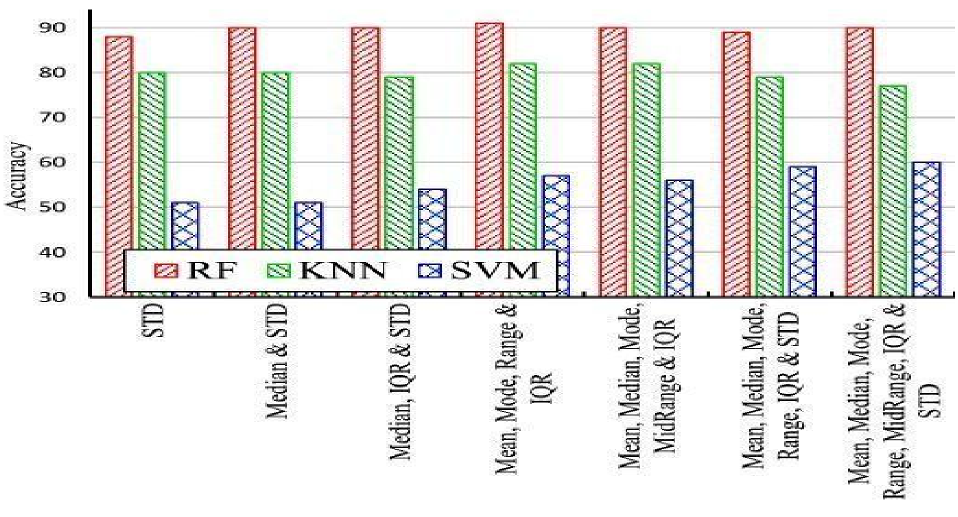


Figure 12

Result of search process for selecting feature.

Seven intensity moments i.e. Mean, Median, Mode, Midrange, Range, IQR, and Standard deviation are used for extracting the features from the image applying respective formulas. Calculating these seven features a total of 127 com- binations (7C1+7C2+7C3+7C4+7C5+7C6+7C7) is evaluated for each classifier (KNN, SVM, and random forest), which is called an exhaustive search process. An exhaustive search process assists to intuit which combination is best for this dataset. It also helps to find out which classifier is suitable for obtaining the best result. Fig 3 shows that Mean, Mode, Range, and IQR are sufficient to get the best result using a random forest classifier.

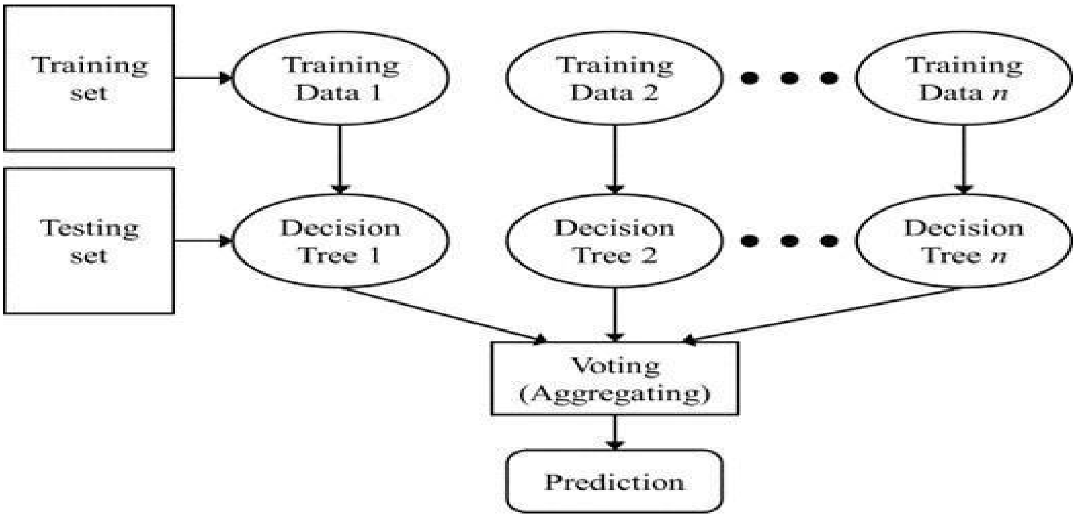


Figure 13
System architecture of random forest decision tree.

Testing Phase

Using the equivalent processes of the training phase the feature of the query images are extracted. After Extracting these features, a feature vector is erected for the query image. This feature vector is redirecting to a classifier name random forest decision tree classifier. Row sampling and feature sampling of rice leaf datasets are consigning through decision trees. That classifier can easily classify what type of disease is containing in the query image.

Classification using Random Forest: Random forest is a supervised ensemble learning algorithm that is applied de- ployed for both classifications as well as regression problems. Usually, the forest is consists of treesand more trees mean a more robust forest. Likewise, the random forest algorithm generates decision trees on data models and then gets the estimate of the diseases from each of them. Many separate learners are created bythis ensemble learning bagging method. Some trees may be incorrect, multiple trees will be correct as a result.

every decision tree has high variance. Aggregation is generated for predictions using the CART (Classification and Reintegration Tree) algorithm. [15]. So as a congregation the trees are capable of taking in the proper direction. Fig 4, represents the system architecture of the random forest decision tree. When the system combines all the decision trees regarding majority vote, thus high variance will get converted through low variance. Because when row sampling and feature sampling are proceeding into the decision tree, it tends to become an expert for these specific rows of the dataset they have. A total of 352 images of sample features from training data went through the decision tree. Before that, we calculate which features are best for this detection process of rice leaf disease. Now, this process will able to give the approximately correct detection, when some query images send to this system. Finally, by the calculation of majority voting, what types of diseases the leaf is containing come out.

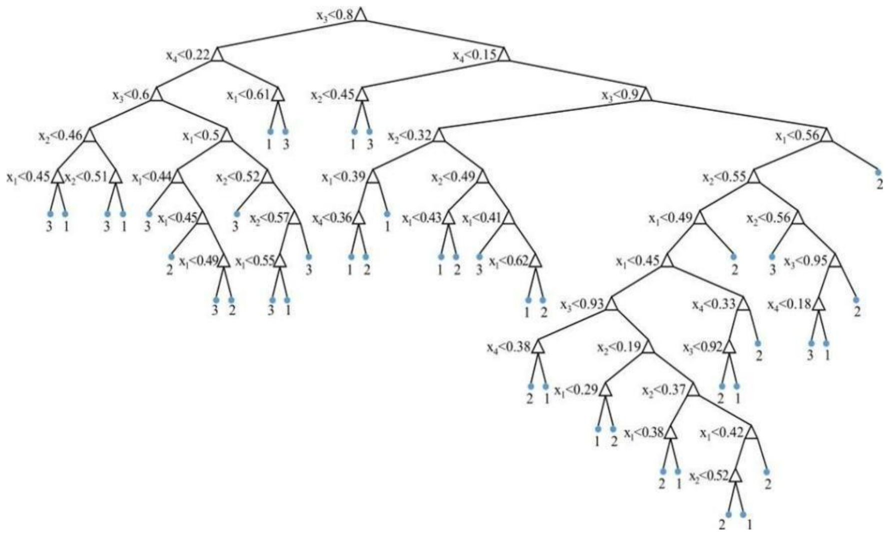


Figure 14
Random forest decision tree for classifying rice leaf diseases.

The left branch value and another branch value is just above or equal to that threshold value. Mean, Mode, Range, and IQR these four features respectively denote as x1, x2, x3, and x4 are utilized to represent the decision nodes of the decision tree. And leaf nodes 1, 2, and 3 respectively present Blight, Blast, and Brown spot disease which is in fig 5.

III. RESULT AND DISCUSSION

The training phase and testing phase are the two main parts of this work. In the training phase, did extract the features of the rice leaf image. Then the feature vector is created and these features are stored in the database as training elements. The testing phase allows to find out how well the images are trained. So, generating the feature vector, the query image is sent to the random forest decision tree classifier for identifying diseases. Correctly classify and misclassification of the Blast, Blight, and Brown spot diseases are respectively 51, 57, 52, and 8, 4, 3. So, the accuracy of each leaf disease and the overall accuracy is shown in Table I. Precision and Recall of the outcome of individual disease and the overall accuracy of the system are exposed in Table II. 91.47% accuracy attained in this proposed system which is pretty good for classifying diseases. If the affected part of the leaf is under consideration this accuracy will be higher.

Confusion matrix displays the real and predicted levels of data of a grouping problem [16]. The total number of predicted class and target class of Blast, Blight, and Brown spot disease are respectively: 52, 57, 52 and 60, 61, 55.

TABLE I: ACCURACY OF THE SYSTEM

Disease Type	Accuracy
Blast	86.66%
	91.47%
Blight	93.44%
Brown spot	94.54%

TABLE II: EXPERIMENTAL RESULT

Disease Type	Precision	Recall
Blast	0.867	0.962
Blight	0.934	0.919
Brown spot	0.945	0.867
Overall Result	0.914	0.916

Normalized confusion matrices are shown in Table III. Disease recognition result: The proposed system identifies disease with 91.47% accuracy. In fig 6, the red label and blue level name respectively indicates the original class and rice leaf diseases that are determined by this system.

(a) Correct detection (b) Correct detection

(c) Correct detection(d) Incorrect detection

Figure 15 Different rice disease detection example.

Performance Comparison: Table IV represents the evalu- ation of this method with some existing works. Prajapati et al.[17] had proposed the dataset which was created manually by separating infected leaves into various disease classes. They had consulted the farmers and then the agriculturist for getting the exact plant disease name. It is to be noted that, the comparative results shown in Table IV are of the different datasets. This is because no benchmark dataset or source implementation was available to experiment on the same ground. Since it is burdensome to accurately implement the state-of-the-art methods on this dataset, we presented the results here to get an overview of how different methods perform on a similar type of dataset. It can be seen that the proposed method shows a quite satisfactory accuracy for practical use.

A method for classifying the rice leaf diseases like Blast, Blight, and the Brown spot is designed. This work describes three types of rice leaf disease using a machine learning algo- rithm with high correctness. Rice leaves containing diseases can smoothly identify by using the random forest decision tree. The Matlab application is essential for doing the work. In this implementation intensity moments of the affected part of the rice leaf have been extracted. We will include color, shape, texture features, Hu moment, and test this by some different types of algorithms in future work. Neural networks can be the next step for detecting plant diseases more quickly. By doing some minor modifications this same method can be realistic to identify other leaf diseases.

CHAPTER 4
PROPOSED SYSTEM

I. METHODOLOGY

The proposed plant disease prediction method takes input from the plant's leaves images. Fig. 1 represents the block diagram of the proposed method. Firstly the data is preprocessed by resizing the input images and further a NumPy array is created for the same. Next the dataset and label of all the images are segregated. The model has been trained on a specific data set consisting of images of the different diseased plant leaves which are considered for this study. The labeled data is now stored in pickle files which are again extracted during the training period of the model. For the model, the convolution layers are declared followed by max-pooling layers. After that, 25% of the whole data is dropped out. The output is flattened to feed the dense network. The last layer has a softmax activation to predict the disease of the given leaf. To reduce the loss function Adam optimizer is utilized. The framework consequently distinguishes the picture of leaf given and pre-processes the picture further for prediction. The model will produce 15 distinctive probability values for 15 labels respectively among which the probability value with highest score to the relating name will be the anticipated disease or result for that particular image.

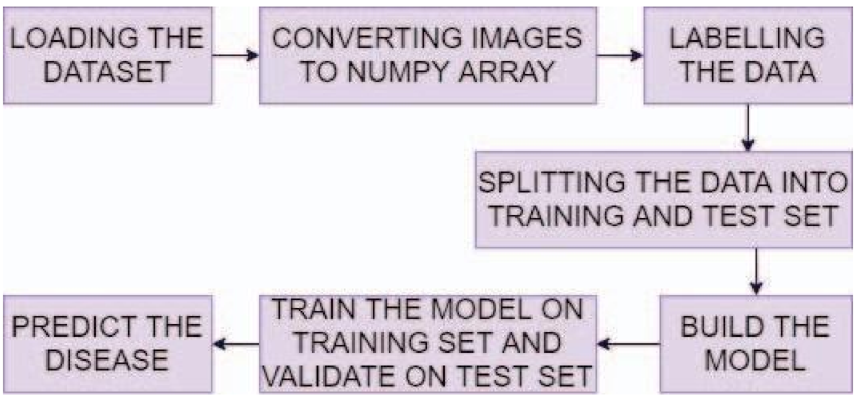


Figure 16
Block diagram of the proposed scheme.

II. CNN

In machine learning, CNN takes a varied approach towards regularization. It is less complicated than conventional models of regularization .The layers are described below.

Input Layer

In this layer input is fed to the model. At this beginning stage of the neural network, the no of neurons and number of features are equal. Considering an image the number of pixels in it is equivalent to the total number of features . The input data is divided into two parts which are used for training and testing the model The major part of data is used for training and the minor part of it is used for testing.

Figure 17
Sample Images from the database (from left to right) Potato Early Blight, Tomato Healthy

Hidden Layer

This layer receives the output from the input layer. It is dependent upon both the model and size of data as well. Number of neurons may vary in each of the hidden layer .

Output Layer

A logistic function receives the data from hidden layer as input The probability score is obtained for each class by converting the output of each class by a logistic function. It coverts each class output into an equivalent probability score for the same. CNN layers are described below. 1.Convolution layer- It is the first layer for dimensions extraction from any input image. Convolution layer consists of filters which help extract particular characteristics, which results into a feature map of the input images. This is a mathematical op\eration which receives two inputs. Input and output information is provided below for this layer.

CNN layers are described below.

Convolution layer

It is the first layer for dimensions extraction from any input image. Convolution layer consists of filters which help extract particular characteristics, which results into a feature map of the input images. This is a mathematical operation which receives two inputs. Input and output information is provided below for this layer. Fig 3 shows rectified linear unit.

Inputs:
An image matrix (volume)of dimension(h*w*d).
A filter (fh*fw*d).
Output:
Output volume dimension (h-fh+1)*(w-fw+1)*1

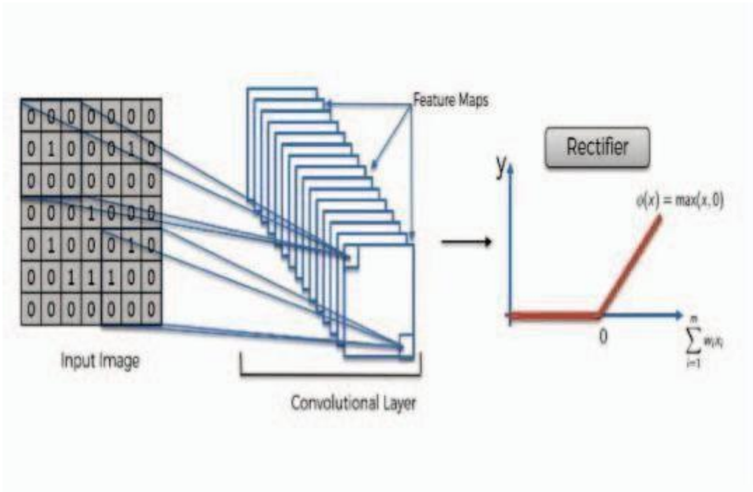


Fig.ure 18

Rectified Linear Unit

Pooling Layer

The pooling layer functions such a way that a 2D filter slides over every channel of the feature map and conveys the features lying within the area enveloped by the filter. Given a specified dimension of any feature map the pooling layer output dimension is expressed as follows

Max Pooling Layer

It is that feature map region from where maximum numbers of elements are selected and hidden by the filter. Thus the max-pooling layer output is afeature map which contains the most prominent features of the preceding feature map. Fig 4 shows maximum pooling layer.

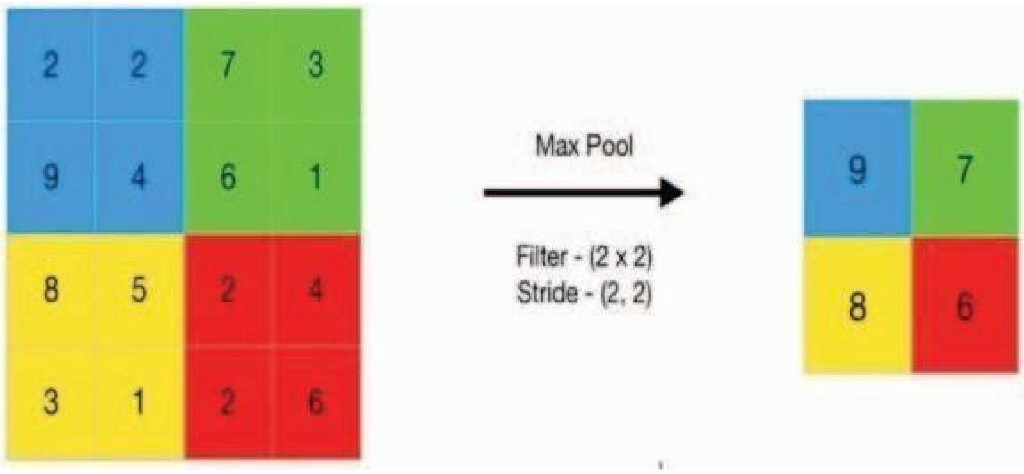


Figure 19
Max PoolingLayer

Fully Connected Layer

The fully connected(FC) layer in the CNN represents the feature vector for the input. It contains crucial information about the input. During the training of the network, this feature vector is further used for classification, regression etc. It is also being used as an encoded vector. During training, this is used to determine the loss and helps the network to get trained. The convolution layers before the FC layers hold vital information about local features in the input image such as edges, blobs, shapes, etc. Each convolution layer holds multiple filters that represent one of the local features. The FC layer detains composite and collectively compiled information from all the convolution layers that matters the most.

Filters and Feature Maps

Filters are not predefined in CNN, rather self-learned by the model itself. In a convolution layer filters learn to detect abstract concepts, like the boundary of a face or the eyes of a person. Severalconvolution layers together can extract in-depth information from an image.

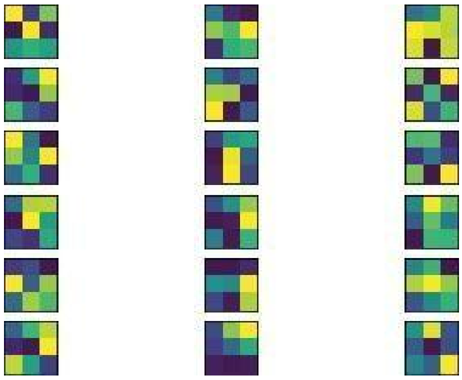


Figure 20

. Visualization of filter for 1st convolution layer.

It is like a membrane that onlyallows desired characteristics to pass from it. Feature mapsare the outputs of filters in the convolution layer. Fig 5-Fig 8 are showing the filter and feature map of 1st and 2nd convolution layer incorporated with 16 GB RAM DDR4, Windows 10, 64-bit operating system.

Total computational time is taken approximately 30 minutes inclusive of 3 minutes of pre- processing the data. The input feed from the webcam right now is not efficient enough to eliminate the background from the given frames but the input image predictions are working fine. A model is overfitted if the difference between its train accuracy and test accuracy is considerably high which is not desired.

Dropout layer has been incorporated after 1st (p=0.25), 3rd(p=0.25), and 5th(p=0.5) layer in the proposed model and the final train accuracy is obtained as 97.42% while test accuracy is 88.80%.

The difference between the two accuracies can be examined to infer that the model is not overfitted Comparative study of this method with the existing method can be shown in Table III. Different performance metrics are calculated and shown in Table IV. From the given comparison it can be said that the proposed method is givingdesired result with better accuracy.

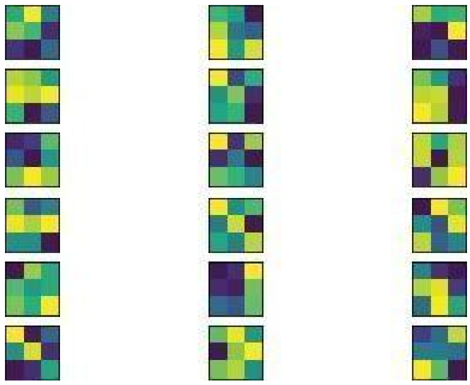


Figure 21
. Visualization of filter for 2nd convolution layer.

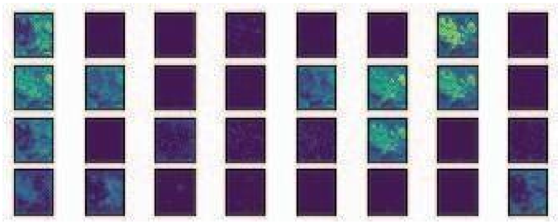


Figure 22
. Visualization of feature map for 1st convolution layer.

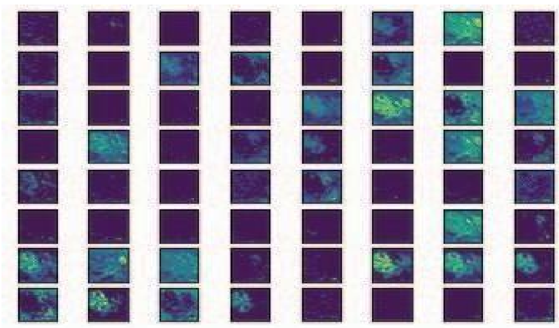


Figure 23
Visualization of feature map for 2nd convolution layer

CHAPTER 5

SYSTEM DESIGN

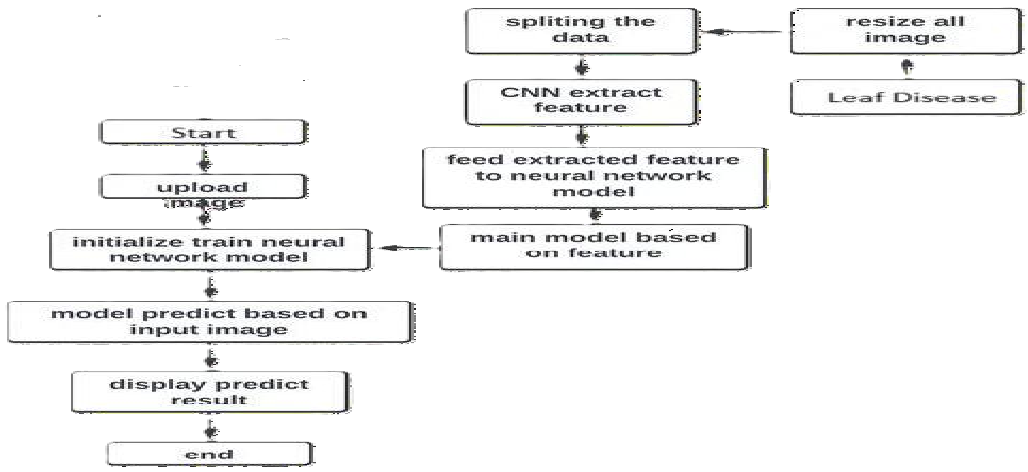


Figure 24
Proposed diagram

1. Introduction: Convolutional Neural Networks (CNNs) are a class of deep neural networks, most commonly applied to analyzing visual imagery. They are particularly well-suited for tasks like image classification, object detection, and image segmentation.

2. Architecture:

- **Convolutional Layers:** CNNs consist of multiple convolutional layers, where each layer applies a set of learnable filters or kernels to input data. These filters slide over the input image, computing the dot product between their weights and the input at every position.
- **Activation Function:** Typically, a non-linear activation function like ReLU (Rectified Linear Unit) follows each convolutional operation to introduce non-linearity into the model.

- **Fully Connected Layers:** At the end of the network, one or more fully connected layers are typically employed to perform high-level reasoning based on the features extracted by the convolutional layers.
- **Softmax Layer:** In classification tasks, a softmax layer is often used to compute the probability distribution over the different classes.

3. Feature Learning:

- CNNs automatically learn hierarchical representations of features from the raw input data. Lower layers capture simple features like edges and textures, while higher layers learn more complex and abstract features relevant to the task at hand.
- The convolutional operation, combined with weight sharing and spatial hierarchies, enables CNNs to capture translational invariance, making them robust to variations in object position within an image.

4. Training:

- CNNs are trained using backpropagation and gradient descent, similar to other neural networks. However, due to their large number of parameters, training CNNs often requires substantial computational resources and data.
- Data augmentation techniques, such as rotation, scaling, and flipping, are commonly employed to artificially increase the size of the training dataset and improve model generalization.

5. Applications:

- CNNs have achieved state-of-the-art performance in various computer vision tasks, including image classification (e.g., identifying objects in photographs), object detection (e.g., finding and classifying objects within an image), and semantic segmentation (e.g., labeling each pixel in an image with its corresponding object class).

6. Transfer Learning:

- Due to the high computational cost of training CNNs from scratch, transfer learning is often used, where pre-trained CNN models (trained on large-scale datasets like ImageNet) are fine-tuned on smaller, task-specific datasets.

RESNET

- **Skip Connections (Residual Connections):** The core innovation of ResNet is the introduction of skip connections that bypass one or more layers. These connections allow the gradient to flow directly through the network, alleviating the vanishing gradient problem. Instead of trying to learn the desired underlying mapping, ResNet learns the residual mapping; hence, the name "Residual Network.
- **Residual Blocks:** The basic building block of ResNet is the residual block. Each residual block consists of two or more convolutional layers, followed by batch normalization and ReLU activation functions. The skip connection adds the original input to the output of the convolutional layers. There are different variants of residual blocks, such as basic residual blocks and bottleneck residual blocks, depending on the number of convolutional layers and computational efficiency requirements.
- **Deep Architectures:** ResNet architectures are designed to be extremely deep. The original ResNet paper introduced variants with 34, 50, 101, and 152 layers. Subsequent research has explored even deeper architectures, such as ResNet with over 1000 layers, known as "ResNet-1001" or "ResNet-1202."
- **Global Average Pooling:** ResNet typically uses global average pooling (GAP) instead of fully connected layers at the end of the network. GAP helps reduce overfitting by reducing the total number of parameters and introduces spatial features.
- **Pre-Activation Residual Units:** In the later versions of ResNet, the authors introduced pre-activation residual units, where batch normalization and ReLU activation are applied before convolution operations. This modification helps with gradient propagation and facilitates the training of even deeper networks.
- **Applications:** ResNet architectures have achieved state-of-the-art performance on various computer vision tasks, including image classification, object detection, semantic segmentation, and image recognition tasks in various domains.
- **Transfer Learning:** Pre-trained ResNet models, trained on large-scale datasets like ImageNet, are widely used for transfer learning. Researchers and practitioners fine-tune these pre-trained models on smaller datasets for specific tasks, saving time and computational resources.

- ResNet addresses this problem by introducing skip connections, also known as shortcut connections or identity mappings. These connections allow the gradient to bypass one or more layers, effectively "shortcutting" the learning process. Instead of directly trying to learn the desired underlying mapping, ResNet learns the residual mapping—the difference between the input and the output of a layer. This residual mapping is then added back to the input of the layer, allowing the network to learn the desired underlying mapping more easily.

- The key innovation of ResNet is the use of residual blocks, which consist of several convolutional layers followed by a shortcut connection that adds the original input to the output of the convolutional layers. These residual blocks enable the training of very deep neural networks, reaching depths of over a hundred layers while maintaining or even improving performance.

- ResNet architectures come in various depths, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, with the number indicating the total number of layers in the network. These architectures have been widely adopted in various computer vision tasks, including image classification, object detection, and segmentation, due to their effectiveness in learning hierarchical features from visual data.

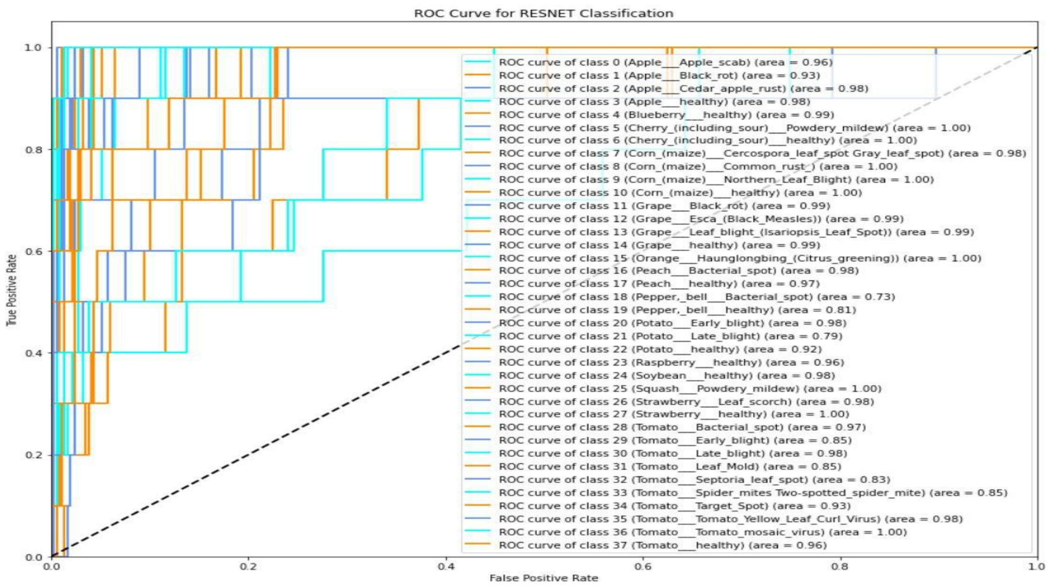
Residual Learning: Instead of trying to learn the underlying mapping directly from the input to the output of each layer, ResNet learns the residual mapping—the difference between the input and the output of a layer. This is based on the hypothesis that it is easier to learn the residual mapping than to learn the underlying mapping directly The basic building block of ResNet is the residual block. Each residual block typically consists of two or more convolutional layers followed by a shortcut connection. The convolutional layers perform feature extraction, while the shortcut connection skips one or more layers by adding the original input to the output of the convolutional layers. Mathematically, the output of a residual block H(x)H(x) is computed as:

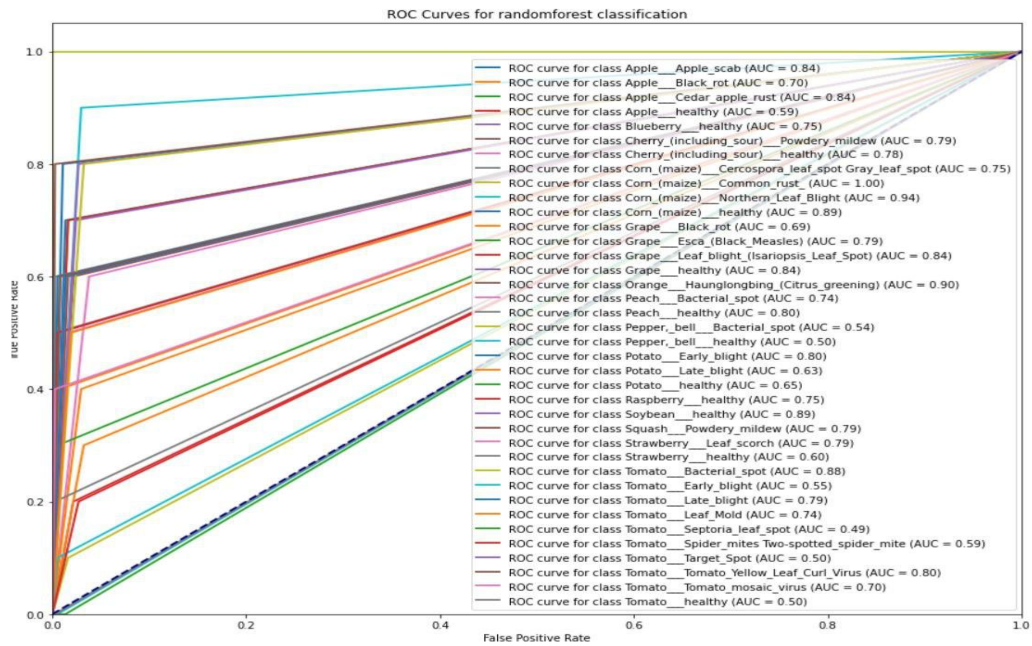
$$H(x)=F(x)+xH(x)=F(x)+x$$

where xx is the input to the block, F(x)F(x) represents the residual mapping learned by the convolutional layers, and H(x)H(x) is the output.

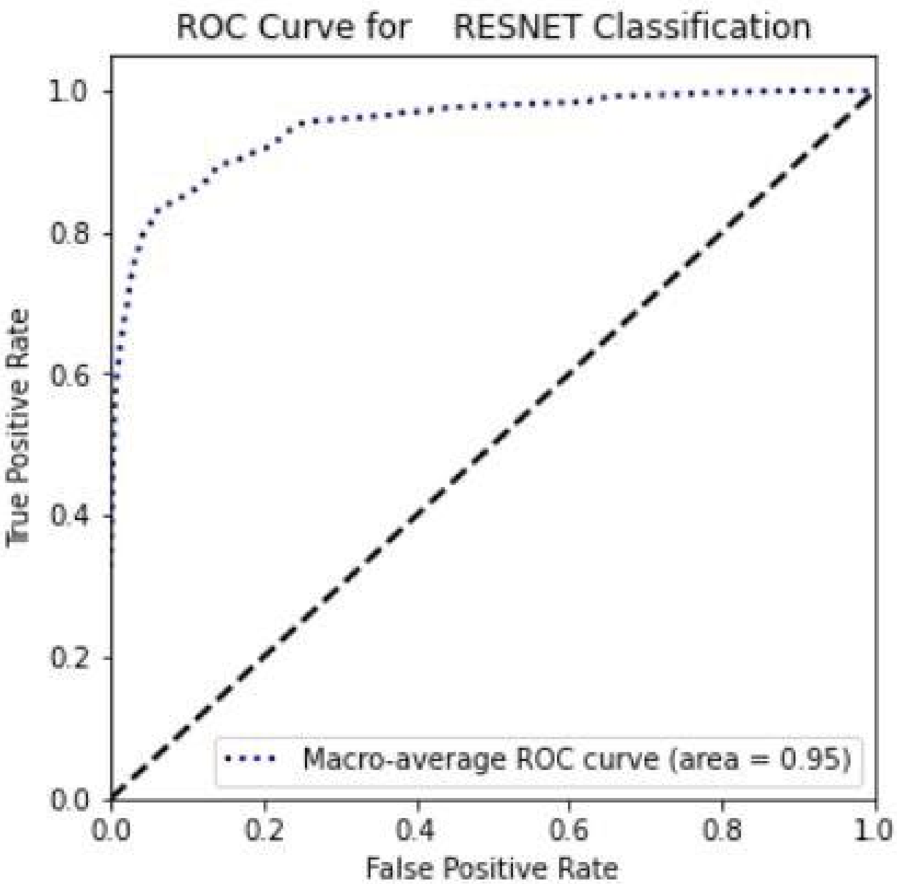
CHAPTER 6
RESULT ANALYSIS

ROC CURVE



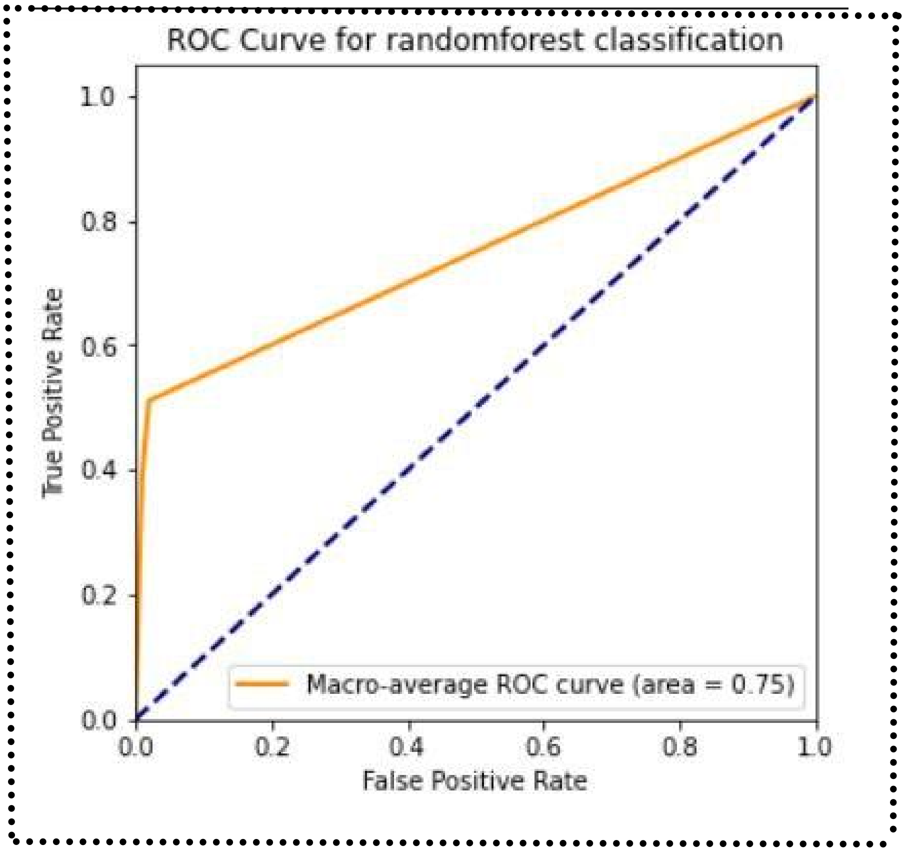


DIFFERENCE



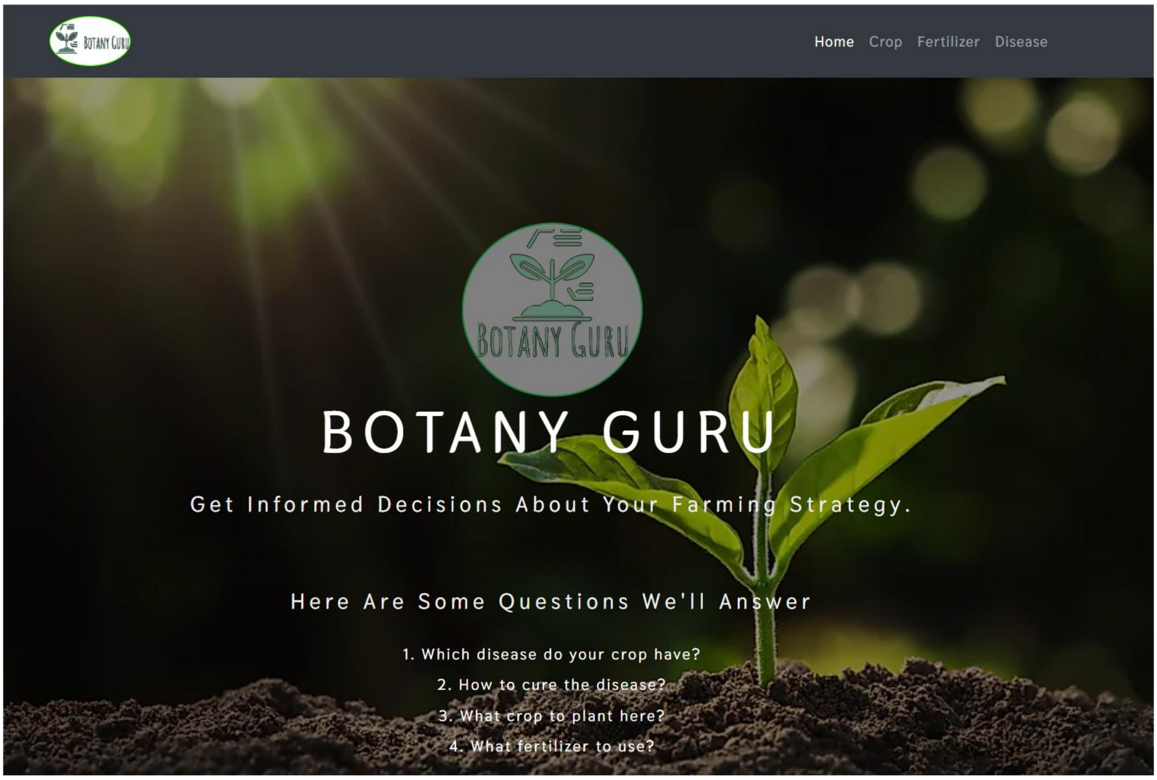
- **True Positive Rate (Sensitivity):** This is the proportion of actual positive cases that are correctly identified by the classifier. In the context of ResNet classification, it represents the percentage of correctly classified positive (e.g., correctly identified as the target class) instances among all positive instances.
- **False Positive Rate:** This is the proportion of actual negative cases that are incorrectly classified as positive by the classifier. In ResNet classification, it represents the percentage of incorrectly classified negative instances among all negative instances.
- **Threshold:** The ROC curve is created by varying the threshold for classifying instances as positive or negative. At each threshold, the true positive rate and false positive rate are calculated, resulting in a point on the ROC curve.

- **Area Under the Curve (AUC):** The AUC represents the overall performance of the classifier. It measures the area under the ROC curve, with values ranging from 0 to 1. A higher AUC indicates better performance, where an AUC of 1 represents a perfect classifier and an AUC of 0.5 represents a random classifier.

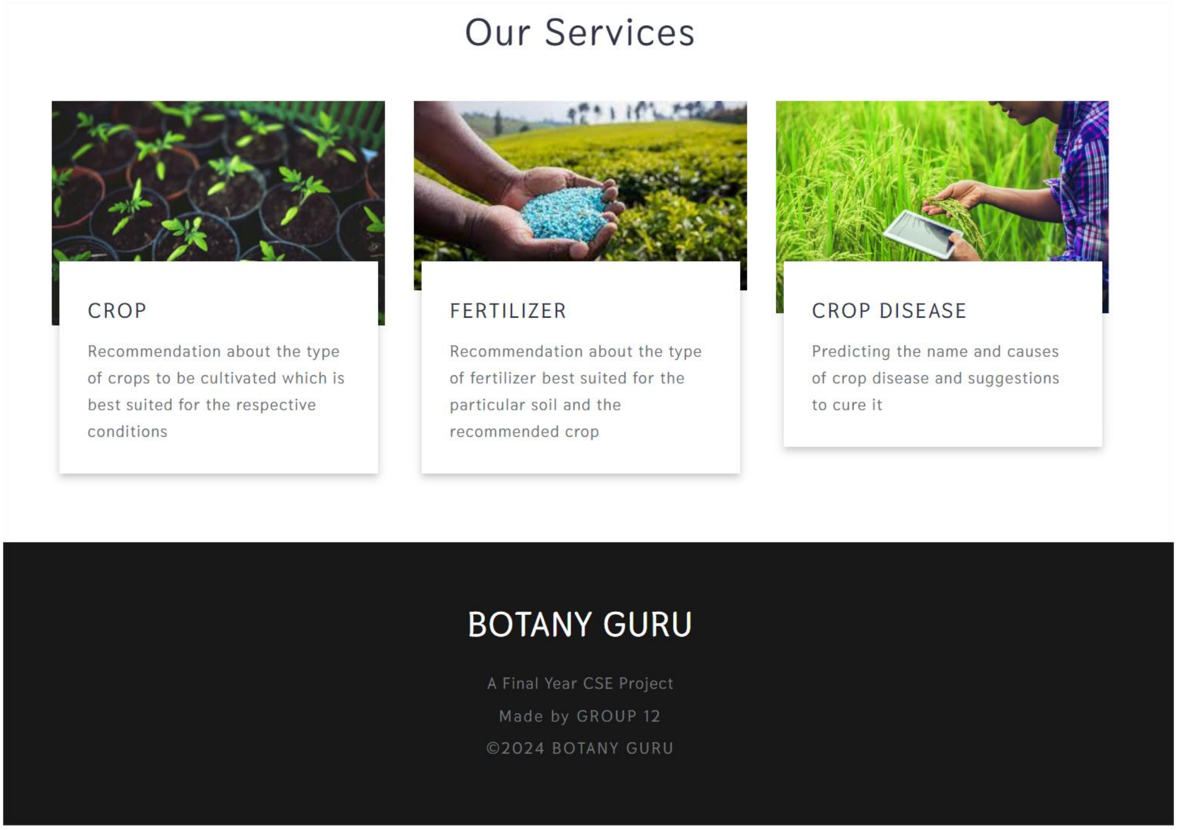


- **True Positive Rate (Sensitivity):** Just like in any binary classification task, the true positive rate in the context of Random Forest classification represents the proportion of actual positive cases that are correctly identified by the classifier. In other words, it indicates how sensitive the Random Forest model is in correctly identifying positive instances.
- **False Positive Rate:** This is the proportion of actual negative cases that are incorrectly classified as positive by the Random Forest classifier. It represents the model's tendency to misclassify negative instances as positive.

- **Threshold:** Similar to other classifiers, the ROC curve for Random Forest is created by varying the threshold for classifying instances as positive or negative. At each threshold, the true positive rate and false positive rate are calculated, resulting in a point on the ROC curve.
- **Area Under the Curve (AUC):** The AUC of the ROC curve for Random Forest classification represents the overall performance of the model. It measures the area under the ROC curve, with values ranging from 0 to 1. A higher AUC indicates better performance, where an AUC of 1 represents a perfect classifier and an AUC of 0.5 represents a random classifier.



This is the home page,"Welcome to Botany Guru,


Our Services
CROP
Recommendation about the type of crops to be cultivated which is best suited for the respective conditions
FERTILIZER
Recommendation about the type of fertilizer best suited for the particular soil and the recommended crop
CROP DISEASE
Predicting the name and causes of crop disease and suggestions to cure it
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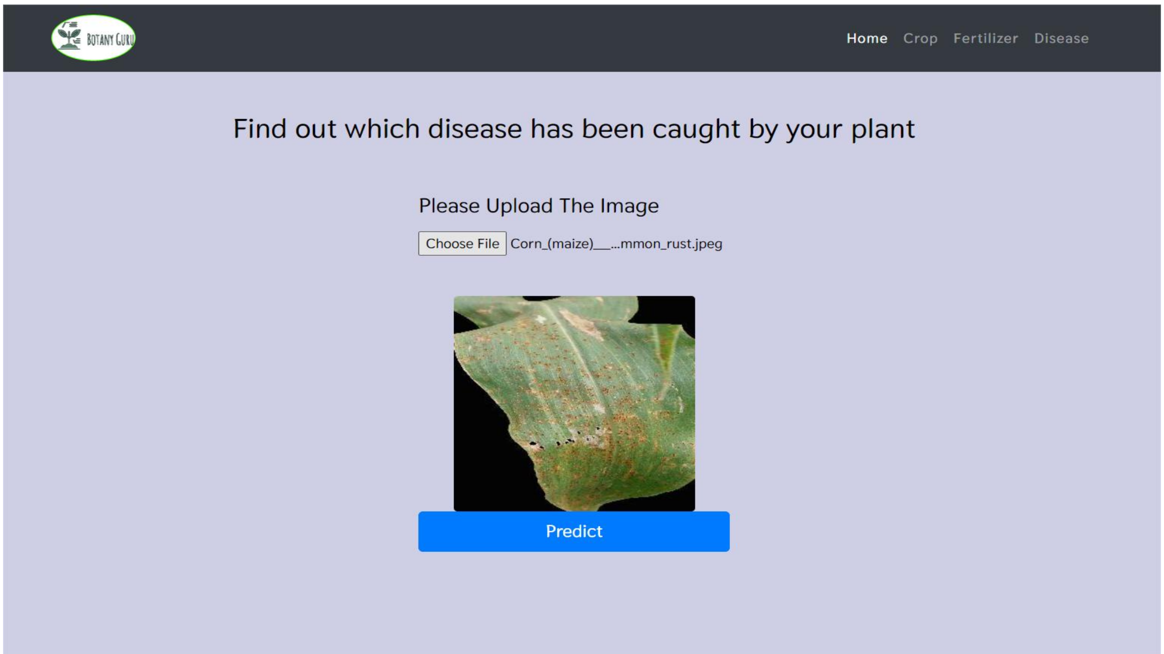

Home
Crop
Fertilizer
Disease
Find out which disease has been caught by your plant
Please Upload The Image
Choose File
Corn_(maize)___...mmon_rust.jpeg
Predict

- **Maize Dwarf Mosaic Virus (MDMV)**: This viral disease is transmitted by aphids and affects corn plants by causing stunted growth, yellowing of leaves, and mosaic patterns on leaves. Severe infections can lead to reduced yield and poor grain quality.

- **Stalk Rots**: Various fungi, including Fusarium, Colletotrichum, and Diplodia species, can cause stalk rots in corn. Symptoms include soft, discolored areas on the stalk, which can lead to lodging and yield loss

Crop: Corn(maize)

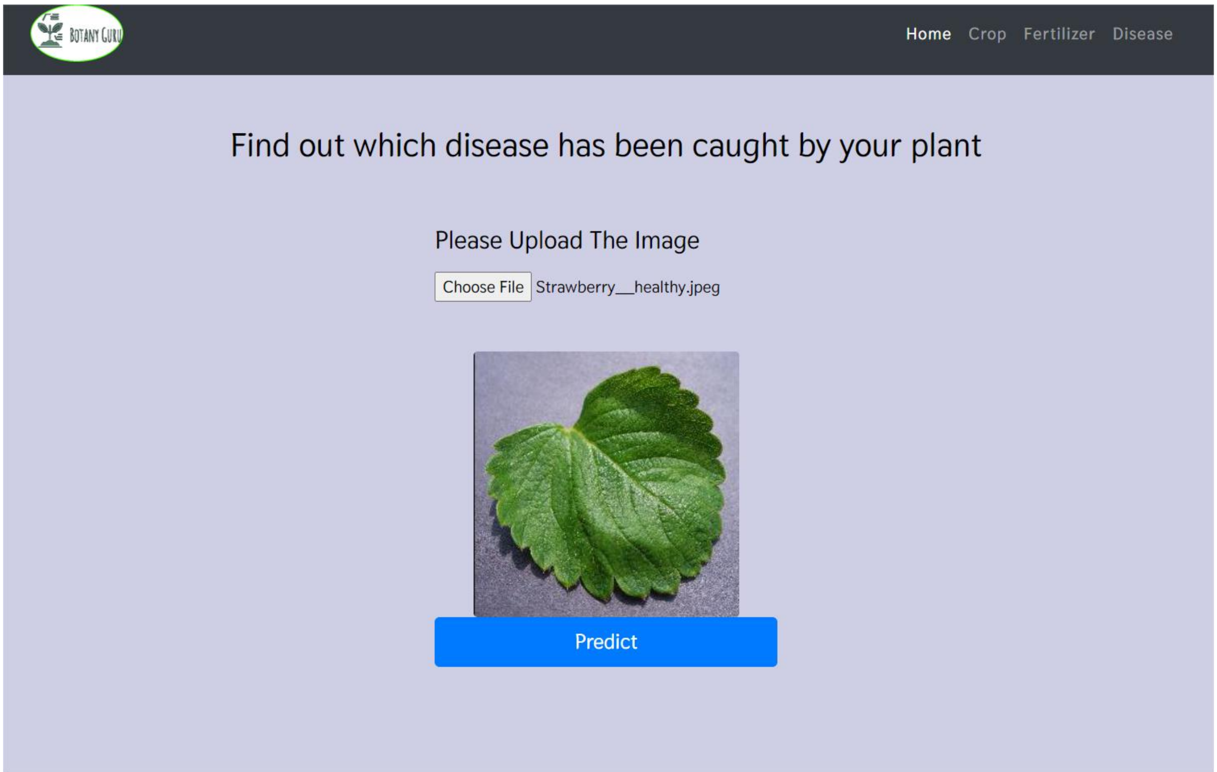
Disease: Common Rust

Cause of disease:

Common corn rust, caused by the fungus Puccinia sorghi, is the most frequently occurring of the two primary rust diseases of corn in the U.S., but it rarely causes significant yield losses in Ohio field (dent) corn. Occasionally field corn, particularly in the southern half of the state, does become severely affected when weather conditions favor the development and spread of rust fungus

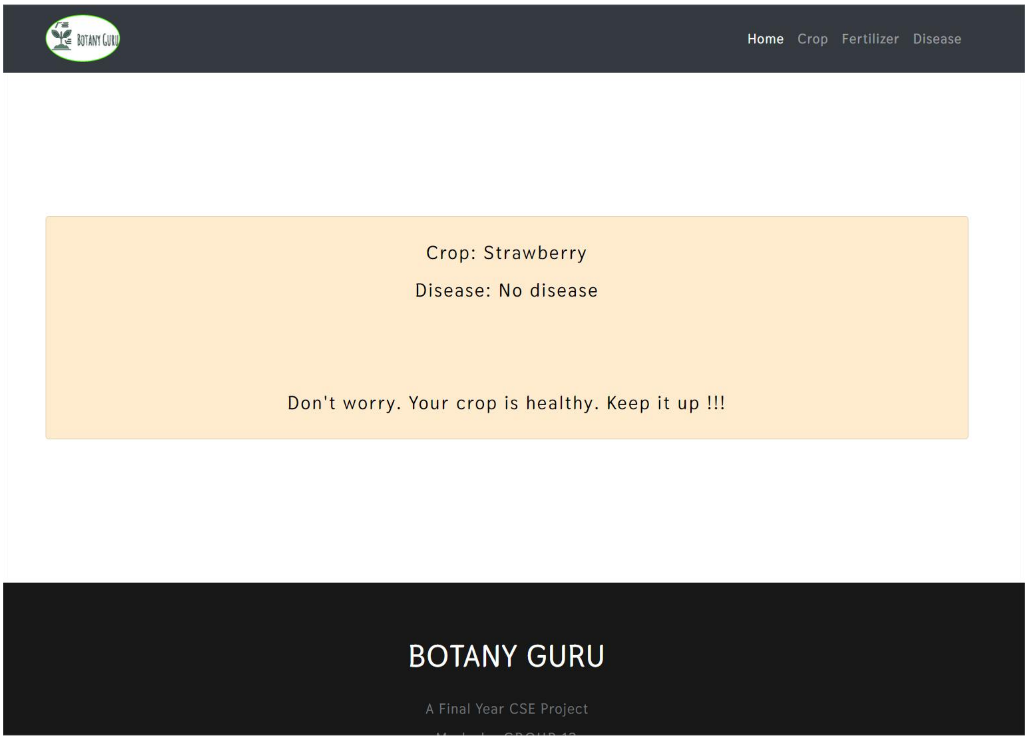
How to prevent/cure the disease

1. Although rust is frequently found on corn in Ohio, very rarely has there been a need for fungicide applications. This is due to the fact that there are highly resistant field corn hybrids available and most possess some degree of resistance.
2. However, popcorn and sweet corn can be quite susceptible. In seasons where considerable rust is present on the lower leaves prior to silking and the weather is unseasonably cool and



Powdery mildew is caused by various fungal species, such as Sphaerotheca macularis and Podosphaera aphanis. It appears as a white powdery growth on the leaves, stems, and sometimes fruit of strawberry plants. Severe infections can lead to leaf distortion, reduced photosynthesis, and decreased fruit yield.

Gray Mold (Botrytis Fruit Rot): Gray mold is caused by the fungus Botrytis cinerea. It affects ripe and overripe strawberries, causing them to develop grayish-brown fuzzy mold. Gray mold can lead to significant fruit rot, especially in wet and humid conditions.


Home Crop Fertilizer Disease
Crop: Strawberry
Disease: No disease
Don't worry. Your crop is healthy. Keep it up !!!
BOTANY GURU
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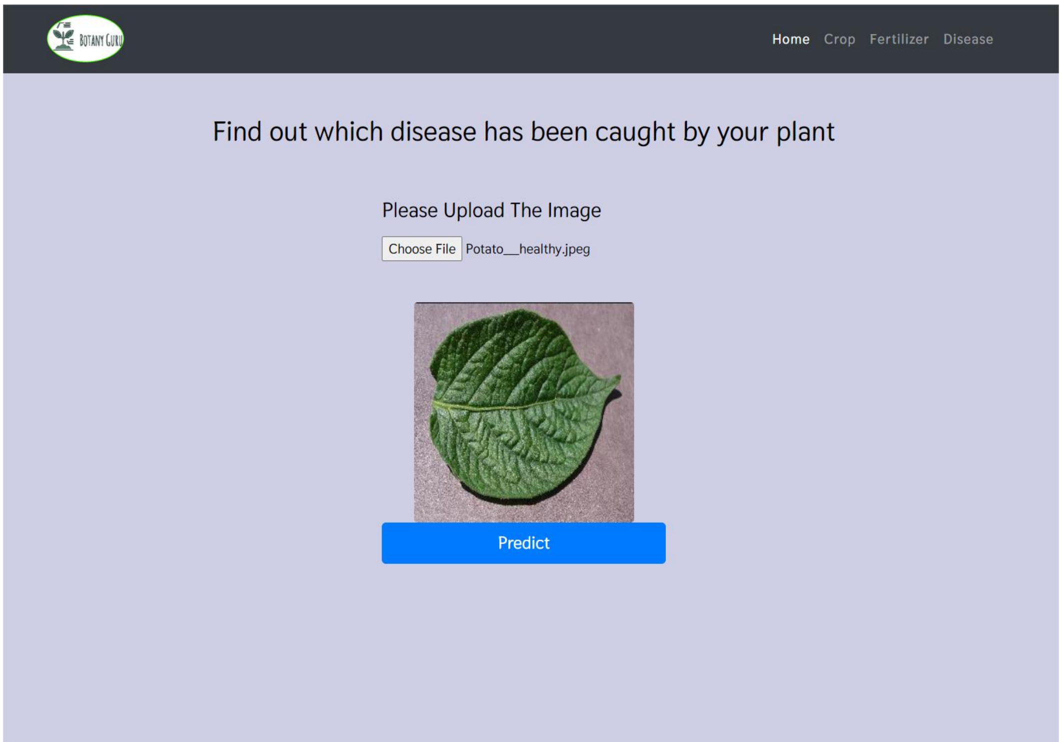
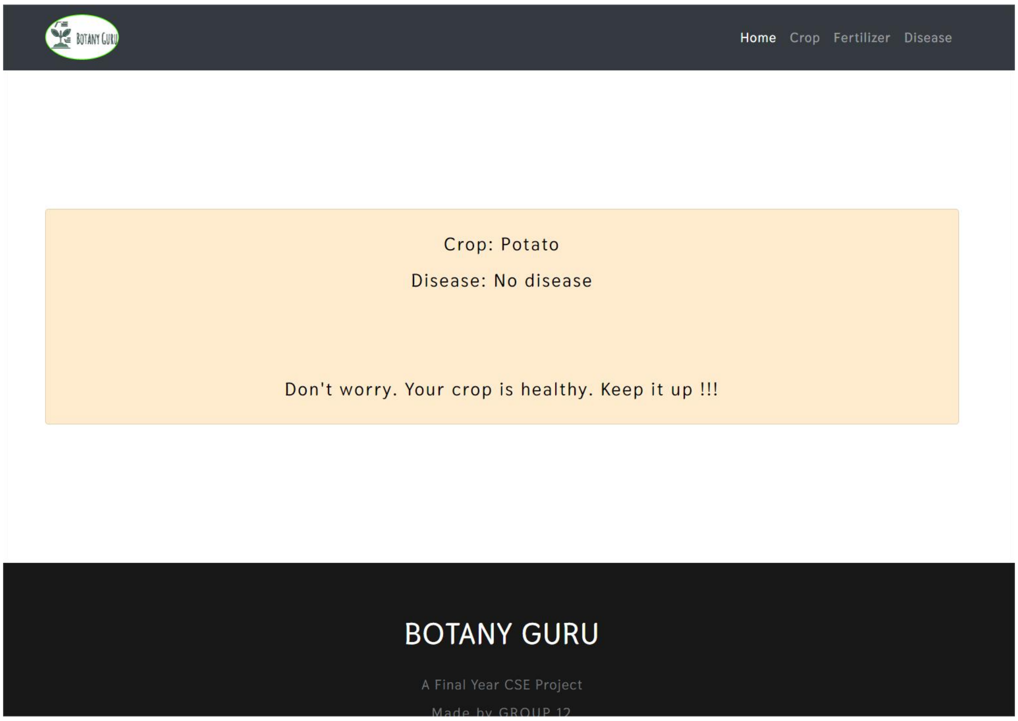
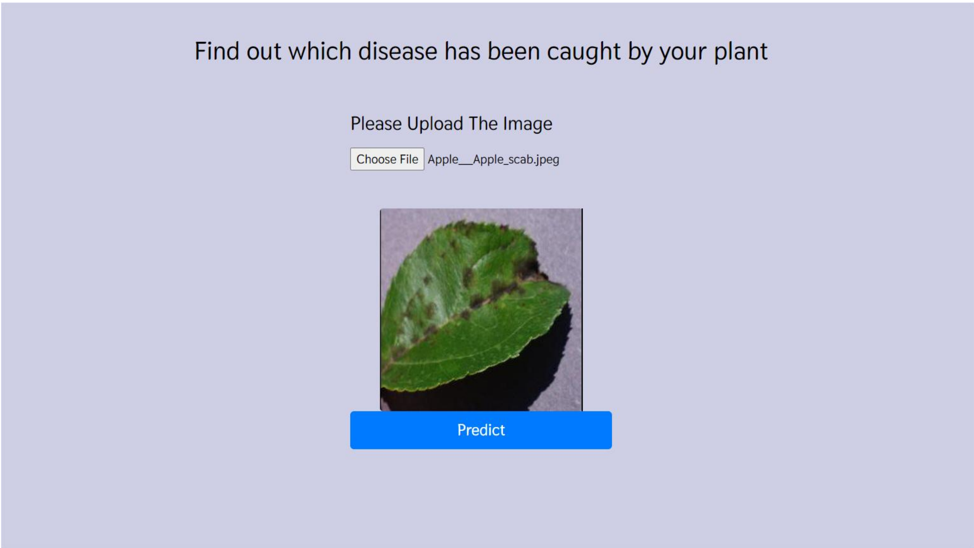

Home Crop Fertilizer Disease
Find out which disease has been caught by your plant
Please Upload The Image
Choose File
Potato__healthy.jpeg
Predict


Home
Crop
Fertilizer
Disease
Crop: Potato
Disease: No disease
Don't worry. Your crop is healthy. Keep it up !!!
BOTANY GURU
A Final Year CSE Project


Find out which disease has been caught by your plant
Please Upload The Image
Choose File
Apple__Apple_scab.jpeg
Predict

- **Apple Scab**: Caused by the fungus Venturia inaequalis, apple scab is one of the most common and economically significant diseases affecting apple trees. It manifests as dark, olive-green or black lesions on leaves, fruit, and twigs. Severe infections can lead to defoliation and reduced fruit quality.

- **Apple Mosaic Virus**: This viral disease can cause mottling, distortion, and yellowing of leaves, as well as reduced fruit quality and yield. It is spread primarily through infected plant material and can be managed through sanitation and planting virus-free stock.This fungal disease requires both apple trees and cedar trees to complete its life cycle. It causes orange, gelatinous lesions on leaves and fruit, which release spores that infect nearby apple trees. Cedar apple rust can lead to defoliation and fruit deformation

Crop: Apple
Disease: Apple Scab

Cause of disease:

1. Apple scab overwinters primarily in fallen leaves and in the soil. Disease development is favored by wet, cool weather that generally occurs in spring and early summer.
2. Fungal spores are carried by wind, rain or splashing water from the ground to flowers, leaves or fruit. During damp or rainy periods, newly opening apple leaves are extremely susceptible to infection. The longer the leaves remain wet, the more severe the infection will be. Apple scab spreads rapidly between 55-75 degrees Fahrenheit.

How to prevent/cure the disease

1. Choose resistant varieties when possible.
2. Rake under trees and destroy infected leaves to reduce the number of fungal spores available to start the disease cycle over again next spring
3. Water in the evening or early morning hours (avoid overhead irrigation) to give the leaves time to dry out before infection can occur.

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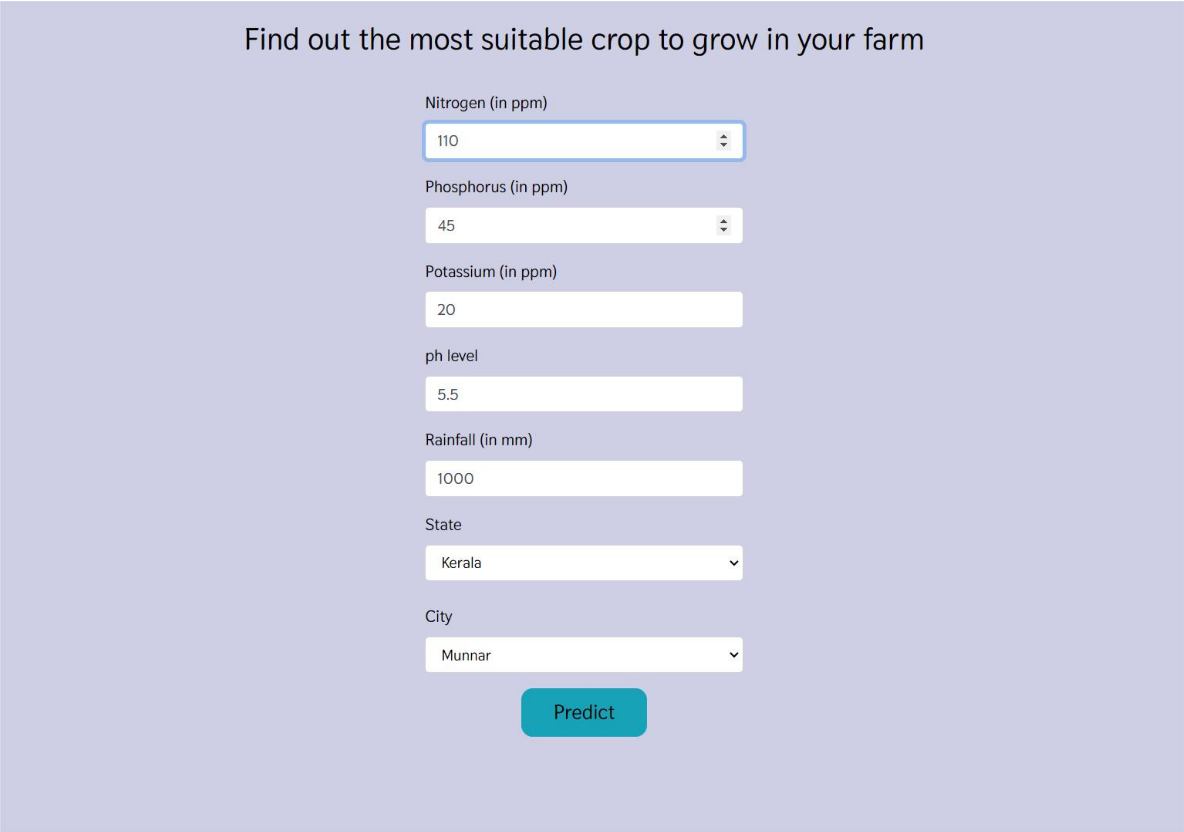
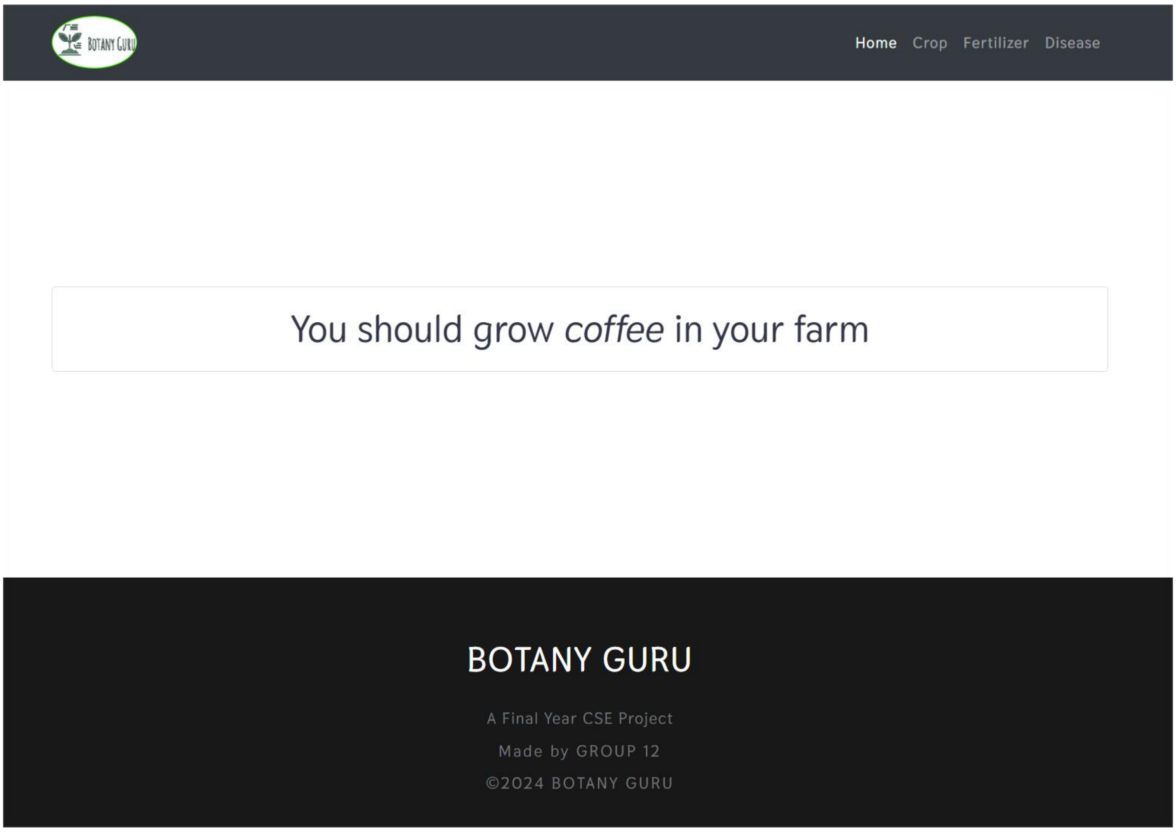
- **Gray Leaf Spot (GLS)**: Caused by the fungus Cercospora zeae-maydis, GLS affects corn leaves, causing small, rectangular lesions with gray centers and dark borders. Severe infections can lead to extensive leaf blighting, reduced photosynthesis, and yield loss.

Crop recomendation system based on soil content present and the weather parameters based on the place.Fertilizer recomendation system based on soil content present and crop that we plant.

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Home Crop Fertilizer Disease
You should grow *coffee* in your farm
BOTANY GURU
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Made by GROUP 12
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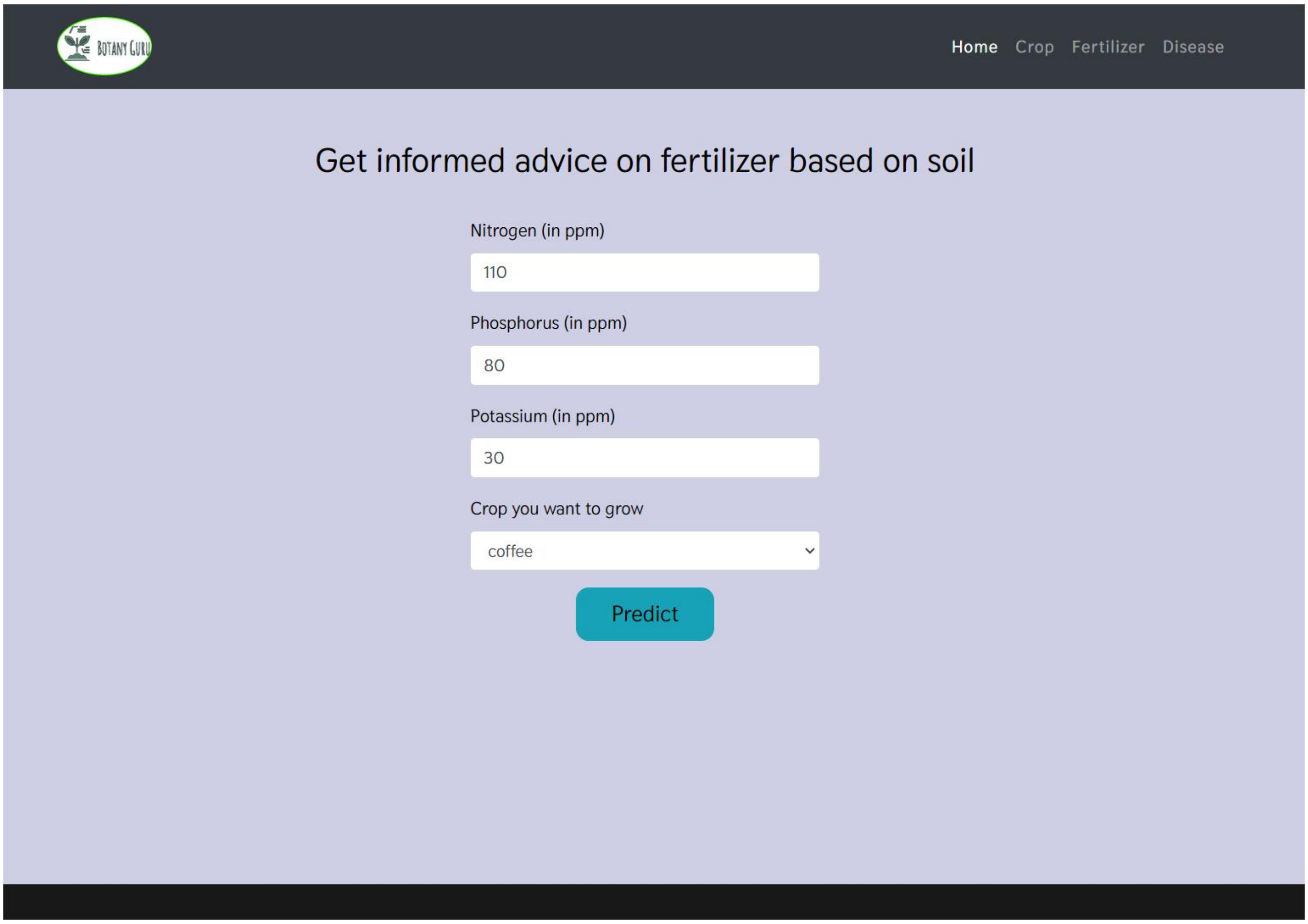
BOTANY GURU
Home
Crop
Fertilizer
Disease
Get informed advice on fertilizer based on soil
Nitrogen (in ppm)
110
Phosphorus (in ppm)
80
Potassium (in ppm)
30
Crop you want to grow
coffee
Predict

The P value of your soil is high.

Please consider the following suggestions:

1. *Avoid adding manure* – manure contains many key nutrients for your soil but typically including high levels of phosphorous. Limiting the addition of manure will help reduce phosphorus being added.
2. *Use only phosphorus-free fertilizer* – if you can limit the amount of phosphorous added to your soil, you can let the plants use the existing phosphorus while still providing other key nutrients such as Nitrogen and Potassium. Find a fertilizer with numbers such as 10-0-10, where the zero represents no phosphorous.
3. *Water your soil* – soaking your soil liberally will aid in driving phosphorous out of the soil. This is recommended as a last ditch effort.
4. Plant nitrogen fixing vegetables to increase nitrogen without increasing phosphorous (like beans and peas).
5. Use crop rotations to decrease high phosphorous levels

CHAPTER 7
CONCLUSION

In conclusion, the integration of machine learning and image processing techniques offers promising solutions for the detection and diagnosis of plant diseases. By leveraging the power of computational algorithms and visual data analysis, researchers and agricultural practitioners can enhance disease management strategies, leading to improved crop health, yield, and food security.

Machine learning algorithms, including convolutional neural networks (CNNs) and support vector machines (SVMs), have demonstrated remarkable capabilities in automatically learning patterns and features from plant images. These algorithms can classify and identify diseased plants with high accuracy, even across diverse environmental conditions and crop varieties.

Image processing techniques play a crucial role in preprocessing and enhancing plant images before feeding them into machine learning models. Techniques such as image segmentation, feature extraction, and image enhancement help isolate diseased regions, extract relevant features, and improve the quality of input data, thereby enhancing the performance of disease detection algorithms.

The combination of machine learning and image processing facilitates real-time and non-destructive monitoring of plant health in agricultural fields. It enables early detection of diseases, allowing for timely intervention and management practices, such as targeted pesticide application, crop rotation, and disease-resistant cultivar selection. This proactive approach can minimize yield losses, reduce reliance on chemical inputs, and promote sustainable agricultural practices.

Furthermore, the scalability and accessibility of machine learning and image processing technologies make them valuable tools for farmers, extension workers, and researchers worldwide. With the development of user-friendly software applications and mobile platforms, these technologies can be deployed in remote and resource-constrained agricultural settings, empowering stakeholders to make informed decisions and effectively combat plant diseases.

In summary, the fusion of machine learning and image processing holds great promise for revolutionizing plant disease detection and management. By harnessing the potential of artificial intelligence and computer vision, we can advance the resilience and productivity of agricultural systems, contributing to global food security and sustainable development efforts.

The project on plant disease detection using machine learning demonstrates the potential for leveraging advanced technology to address critical agricultural challenges.

By harnessing the power of machine learning algorithms and image processing techniques, the project successfully highlights the feasibility of accurate and timely disease identification in plants.

The outcomes underscore the importance of integrating technological innovations with traditional agricultural practices to enhance crop management, minimize yield losses, and promote sustainable farming practices.

CHAPTER 8

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