An Efficient Deep Learning Approach to detect Citrus leaves disease

by

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Bangladesh is one of the leading exporters of citrus. The country has been exporting citrus fruits to more than 60 countries annually. The main risk that citrus disease poses to crop yield is through contact with infected fruit. Identifying different diseases of citrus leaves needs a huge time, work, and expertise. As a result, a new citrus disease detection technology must be developed. Infected crops need to be harvested as soon as possible before they rot. We have developed a useful technique in this study to use deep learning models to detect illness in citrus leaves. Using a unique ensemble approach, we are now able to train the model with different numbers of classes, excluding the best illnesses, and then worked together on the forecast. Each plant's state is determined by taking a snapshot of its leaves and analyzing them. Data collection, pre-processing, segmentation, extraction, and classification are used to detect leaf disease. In this study, plant diseases were identified using photos of their leaves and segmentation and feature extraction algorithms. Our method can predict illnesses with an accuracy of 95% by combining many classifications, which represents a significant opportunity to save production losses.

Keywords: Citrus; diseases; image processing; classification; plant

Dedication

This paper is dedicated to Almighty Allah. We would like to thank all of the member of the group T2210078 for their sacrifice and collaboration during the research process. In the end, it might not be feasible without our parents' unflinching support. It is because of their wonderful words of support and prayers that we are presently getting ready to graduate.

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Chapter 1

Introduction

Flavonoids, fiber, and vitamin C are among the many nutrients present in citrus fruits. Citrus fruits shield the arteries from disease, lessen inflammation, enhance digestive health, and protect against neurological disorders, cancer, and diabetes. Citrus fruits include different kinds of oranges, grapefruit, lemons, and limes. Their soluble flavonoids and fiber may increase HDL cholesterol while lowering triglycerides and LDL cholesterol. Heart disease is at risk due to high blood pressure. Oranges are a byproduct of the orange juice industry and their blooms can also be used to make a variety of fragrant oils. Heart disease is at risk due to high blood pressure.Brazil, China, and Mexico are top producers of orange juice and grapefruit. China is the biggest producer of grapefruit, tangerines and mandarins. Bangladesh's climate is likewise ideal for growing these significant fruits, and daily production is rising. On the other hand,citrus leaf disease brought on by the bacterium Xanthomonas axonopodis, kills citrus trees of all kinds. Insects that scurry around diseased tree leaves and airborne water droplets are the main carriers of the bacteria. Citrus fruit quality could be impacted along with the grower's income as a result. Sick crops need to be removed before they rot, they can spread quickly if they are left on the ground for a long time. In areas with heavy rainfall and high temperatures, citrus canker has the potential to be a deadly diseaseMajor diseases of citrus fruits are blackspot, esca, canker, greening etc. We have choosen to do our research specifically on citrus leaves because there is not many research done specifically on citrus leaf diseases most of the research are on plant diseases.Moreover our homeland is very fertile to produce citrus fruits but unfortunately production is not increasing because of such diseases.

The contribution of this study are: In this study we have develop a disease detection system that can recognize various citrus illnesses using a single system.We have implemented a new ensemble approach which will provide us the opportunity to train the cnn models and dataset classes with distinguishing techniques.Moreover we can say it has given us a chance to train cnn models with anew aproach which has made deep learning models much more effecient.Besides We have found out the best augmentation techniques for a small number dataset indeed we have identified the appropiate best performing cnn models for citrus leaves diseases detection. Additionally, Our research has show how to use essential pesticides and insecticides to stop further assaults. It will be accomplished using Segmentation, Resizing. Furthermore, understandable AI algorithms have been used to analyze the outcome. Finally, an App has been built to predict diseases. Making highly accurate assumptions that can, for example, predict which climate or season there can be a surge of certain diseases can help to improve means that, once the disease detection approach is fully functional, many excellent suggestions can be found and implemented on how it is taking its course of action.

The following sections make up the bulk of this paper.Chapter II refers to some relevant publications on image recognition.The Classification of diseases is primarily introduced in chapter III. The Implementation part is shown in chapter IV. Finally, we reach a conclusion in Section V.

Chapter 2

Literature review

2.1 Related Work

This article demonstrates how image processing can be utilized to detect disease in citrus leaves. We're focusing on implementing effective systems for detecting diseased leaves, which will help us reduce crop losses and increase output. The present state of deep neural network techniques for identifying plant diseases is discussed in this section.

According to [1] substantial quantity of waste is produced annually, with citrus manufacturing companies discarding 50 percent of citrus peel annually due to several plant diseases. Approaches for the automated identification and categorization of illnesses in citrus plants are continuously being developed. For this, authors researched six important citrus diseases. They experimented with a few methods, including citrus detection methods, preprocessing-based methods, segmentation-based methods, feature extraction-based methods, and classifier-based methods. They demonstrated the degree of accuracy for each approach and discussed the advantages and disadvantages of the Classifier-based technique. The most used method for segmenting diseased plants is K-means. Additionally, the image's portrayal of sickness makes the textural elements stand out the most. SVM and NN use these traits to identify illness on citrus leaves that are not infected.

Added to that, they have faced some challenges. For citrus and other plant diseases, the color, texture, and form characteristics are retrieved. They have shown in a table that each feature type has distinct benefits and downsides. These shortcomings reduce the system's accuracy. The feature extraction phase faces a number of difficulties, such as the large dimension of extracted features, irrelevant features, lengthy calculation times, duplication between extracted features, variation in illumination conditions, and strong correlation. These difficulties have a direct impact on system effectiveness.

Learning through visualization of the machines requires high-speed processors to able to detect subtle changes and keep the data in track. Along with that algorithm is also required. Powerful cameras r required that takes multiple snaps with high resolution. Deep Learning algorithms should be implemented. To make it cost effective we can Mobile Net or self-structured classifiers to check and see in which stage the disease is.The most effective CNN detectors can be used if we desire great accuracy (well in this scenario for agriculture engineering). Using our CCL'20 dataset, we created and improved the following algorithms to identify citrus leaf diseases: YOLOv4, CenterNet, Detectors, Faster-RCNN, Cascade-RCNN, Deformable Detr and Fovea Box. The effectiveness of these models in identifying various phases of citrus leaf diseases is evaluated through extensive performance and computational analysis. CNN detectors for citrus leaf disease detection are rated according to their recall and precision, as well as other important factors including training parameters, inference time, memory use, speed, and accuracy trade-off for each model.

According to [2] because it poses a potentially dangerous threat to the citrus industry, citrus canker is a disease that is of global concern. Citrus canker infection causes defoliation, premature leaf and fruit drop, die-back and eventually the plants will never bear any fruit. Leaf spots are the predominant symptom of citrus canker. About 7 to 10 days after infection, leaf lesions become apparent. It is simple to mistake the changes that occur in lesions as they get older for symptoms of other citrus illnesses like citrus scab disease. To segregate citrus lesions from their background, the most important characteristics of the lesions are chosen using an updated AdaBoost algorithm. The distribution of canker zones' local textures and colors are combined to form a suggested canker lesion description.

Although Indian farmers have a wide range of options for healthy foods made from ground crops, it can be challenging to identify plant illnesses in their early stages of growth. In this study of [3] got a solution mostly using the Markov model. With the use of image processing, leaf diseases may be diagnosed. The diseased portion of the citrus leaf may be separated and classified with the use of image processing tools. For more accurate plant disease diagnosis, we need do more study and utilize digital image processing.

[4] reviews several image processing techniques for detecting plant diseases. Scratches such anthracnose, scab, greening, black spot, melanosis, downy mildew, and canker infest citrus plants. Citrus fruits have considerable advantages in that they are anti-mutagenic and antioxidant. Citrus lesions may be found using a number of different methods, including as active contour, edge tracking, clustering, watershed, saliency, thresholding, and a few more. Ten distinct plant diseases were examined by Revathi and Hemalatha, including bacterial blot, late scorch, sunburn, fungal streaks, late blight, sooty mold early, etc.To accurately diagnose illnesses, they retrieved traits related to color, structure, and texture. They then employed a support vector machine classifier. The following approaches have been applied in this survey: K-means Clustering, Histogram matching, region-based, edge detection, fuzzy techniques, and Otsu Thresholding. Colors have a lot of variation, making segmentation operations difficult. The volume of the fruits as well as changes in disease portion size were taken into account. The preprocessing stage reduces the visibility of the disease region in the image compared to the original image displayed in the article. The challenges of picture pre-processing include low-intensity input photographs, noisy foregrounds from achene coverings, changes in illumination, several related severances with hundreds of various frequency ranges, and [5] obtaining the greatest contrast between the backdrop and the fruit covering. These difficulties have

a considerable influence on the accuracy of sickness segmentation. The literature describes a number of pre-processing techniques, including top-hat filtering, color spaces, median filtering, etc.

[6] all in review It is hypothesized that citrus greening, also known as Huanglongbing (HLB) or yellow dragon illness, first appeared in China. One of the most harmful and fatal citrus diseases in the world is HLB. The illness is not identified by the available molecular diagnostic techniques early enough to halt its spread. Although the polymerase chain reaction (PCR) approach may be used to confirm HLB infections, it is costly and hence not practical or cost-effective for wider regions.Fruits and vegetables may be examined using hyperspectral reflectance imaging to detect illness, deficits, and flaws. Melanose, greasy patch, and insect damage all reflected light similarly to canker. These three disorders were more susceptible to misclassification than other types of peel problems. For the detection of illnesses in other crops, such as lettuce and rice, hyperspectral imaging has been utilized. Spectrum angle mapping (SAM), MTMF, image-derived spectral library, hyperspectral pictures, observations from ground measurements, and LSU techniques in the imaging program were used to identify areas of HLB infection (ENVI). The n-D scatter plot of the MTMF analysis for the images taken in 2007 revealed that not all of the pixels were identified as pure endmember pixels. Not all vegetation pixels were spectrally clear, and their pixel values varied from the left to the right of a tree row across a canopy. Additionally, because to the similarity in the spectra of healthy and HLB-infected tree pixels at the canopy edge, the findings of the MTMF and SAM analyses caused false positives, which meant that healthy pixels were incorrectly identified as in feted. An average accuracy of roughly 60 percent was discovered using SAM. There is a clear chance that georeferencing inaccuracy may result in faulty ground truthing data. Furthermore, only one to two pixels of location precision for the airborne hyperspectral images were promised. By addressing light variation and normalizing canopy edge pixels, improved atmospheric correction algorithms would help deliver better outcomes. More accurate ground truth data might be used to further confirm the results.

[7]represents Fruits of the citrus family are renowned for their flavor and nutritional benefits. The quality and quantity of citrus fruits are significantly impacted by a number of illnesses. It has been suggested to use feature fusion and transfer learning to categorize citrus fruit illnesses. The criteria are used to group six separate citrus plant diseases.The fused feature set (WOA) is optimized using the Whale Optimization Technique, a meta-heuristic algorithm, for each illness. The suggested method produces better results and achieves a classification accuracy of 95%. A broader dataset made up of several different fruits can be utilized to classify various illnesses. Additional deep learning models and other feature selection methods can be employed for classification to further improve accuracy and computational efficiency.

[8] The implementation of image analysis and classification algorithms for the extraction and categorization of leaf diseases is the goal of this effort. The suggested framework is divided into four sections: feature extraction, picture augmentation, segmenting the region of interest using K-mean clustering, and image pre-processing,

which includes converting RGB to other color spaces. Diseases may affect several components of plants, including the fruit, stem, and leaves.Atypical leaf development, color distortion, stunted growth, and shriveled and damaged pods are typical signs. Several image processing methods to isolate the sick portion of the leaf are presented in this research. Lab and Ycbcr color spaces provide K-mean clustering for disease component extraction using clusters, and SF-CES offers greater color picture improvement. Then, for additional categorization reasons, GLCM texture features and color texture characteristics are retrieved. SVM-based classification is the last step.

In this study [9] The most prevalent is citrus canker disease, which reduces the fruit production of citrus plants like lemons. When the illness infects the plant, it results in a considerable loss in both quality and quantity. The impact on nations whose economy are strongly reliant on agriculture may be negative. The suggested approach makes use of lemon leaves for the classification of citrus canker disease. The CLAHE enhancement approach, which improves picture quality and may be used to diagnose citrus canker disease, was the subject of this study. The sample leaves are separated into numerous pieces after being photographed. Then, in order to diagnose the leaf illness, GLCM color and texture characteristics are extracted using SVM classifiers. The results of the experiments demonstrate that our enhancement model works better than the state-of-the-art picture enhancing methods and that canker detection-based classifiers accurately identify and categorize the canker leaf disorders. The proposed methods are evaluated and contrasted, among others, with K-NN and Navies Bayes classifiers.

According to [10] After a few years, the entire state of Florida caught the HLB infection, which was first identified in a groove in South Florida. Numerous nations in Africa, Asia, and South America have had a harmful impact from HLB on their citrus businesses. After plants were grafted with a disk from another HLB-affected leaf, time-lapse photographs of citrus leaves were taken on a weekly basis to track changes in the gray values of the photos at various points on a leaf.Citrus leaves with HLB disease were researched at the Citrus Research and Education Center in Lake Alfred, Florida. Researchers from Florida were able to see the hyperabsorption of starch on the leaves as soon as the infection started. A vision-based sensor that has previously been developed was used to take time-lapse polarized pictures of the leaves.

[9] Shoby Sunny and Ruby Peter's project involved applying image processing to identify illness on a plant leaf. The goal of the study is to identify the Canker disease in citrus leaves. The goal of the study is to identify the Canker disease in citrus leaves. The methods used include K-means clustering, color co-occurrence matrix, and histogram comparison. These methods allowed for the detection of Citrus canker. The study covered the several methods for identifying citrus canker disease. Digital image processing techniques may be utilized to diagnose leaf diseases more precisely than conventional methods. Histogram comparison, a matrix of color co-occurrences, and K-means clustering were used to find the sickness.

2.2 Research Problem

Crop ailments are the major cause of decreased crop yields, which costs the economy of the nation money. Citrus is a key source of vitamins A and C all throughout the world. On the other hand, citrus diseases have a negative impact on the amount and quality of citrus fruit. Citrus trees, including those that produce lemons, oranges, grapefruit, and limes, are susceptible to a number of lesions, including anthracnose, greening, scab, black spot, and a few more. Citrus trees in the Middle East are threatened by a variety of diseases, including (Phyllocnistis citrella, lack of elements, scale insect, and others), which have expanded slowly over the years and continue to have an influence on the season owing to improper treatment and pesticide use. Experts can watch and classify the primary citrus illnesses based on their symptoms, but this needs continual monitoring and human observation, which can be error-prone and expensive . Wind-driven rain spreads citrus canker [11]. A more or less round, flattened region with a distinct purple border is a common symptom. Some symptoms resemble a lack of leaves. The growth of yellow veins is the disease's most recognizable sign in citrus.

Additionally demonstrated to reduce feature data dimensionality is principal component analysis (PCA). According to, the support vector machine (SVM) has been shown to be extremely promising for accurately classifying leaf diseases [8]. In [5] we can exactly identify the bacterial virus that infects the young leaves and fruits of citrus trees. To detect diseases of citrus Canker The preprocessing method, segmentation method (it is a process where the digital image is transformed in MATLAB to get a black and white image, so the distinction in color helps to get a fair understanding about the affected area), K-cluster method, and Histogram method (it tends to help to identify the exact location of the disease by intensity) have all been used here. The detection of this condition involves a substantial amount of image processing. With his project, just one sickness has been discovered. Therefore, this would not pick up on the other disorders.

According to [11] Lack of elements, and Scale insects have all been found in citrus trees, and their presence has been identified using the top-hat filter, segmentation, Kmean clustering, and GLCM functions. However, just 80 photographs were utilized for training and 60 images were used for testing, despite the fact that the study was successful. This is insufficient for a project to be deemed successful. Additionally, the Hughes accuracy rate was only about 93.18 percent, which may have been higher .

In paper [10], the Pre-Symptomatic Stage of Citrus Huanglongbing Disease has been identified utilizing Polarized Imaging Technique, a bacterial illness. Here, grafting has been effectively employed. However, despite having the greatest starch intensity observed, which was 5%, plant number 5 did not produce any promising findings. This experiment required the use of 5 plants. Because of this, it is impossible to determine which plants have negatively impacted this endeavor. Here, the overall accuracy percentage was just 81%. Thus, it is clear that the following are the works' limitations:

More optimization may be needed in some cases since the implementation still produces results that are not accurate. A database expansion is also necessary to achieve more accuracy. Additionally, only a small number of diseases have been studied; as a result, the effort has to be broadened to encompass additional ailments. Some of the potential causes of misclassification include the following: In order to cover more instances and more accurately anticipate illness, feature enhancement and additional training samples are needed because disease symptoms vary from plant to plant.

Despite the fact that there has been a limited amount of study on effectively diagnosing citrus infections in the past. But only a small number of disorders were addressed. Additionally, the majority of the research only sought to detect a specific illness. Therefore, there isn't enough productive research to identify several diseases in a single study, and furthermore, they simply discovered the diseases without offering the essential treatment recommendations. So, in order to help farmers, we wish to establish a research project that can cover the majority of citrus illnesses. For our project, we would also use segmentation, resizing, resent, densest, and explainable AI to increase accuracy..

2.3 Research Objective

This study intends to create a disease detection system that can identify multiple types of citrus illnesses with a single system while also demonstrating the essential insecticides and pesticides to avoid further attacks. Using Segmentation, Resizing, ResNet, Densest as well as explainable AI algorithms it will be done. Typically, an image device will capture the images of the leaves and deliver them to a central system for processing via gateways. Diseases in leaves could be recognized in central systems using Segmentation, Resizing, ResNet, Densest as well as explainable AI algorithms. The following are the study's goals:

To gain and have good, clear concept about the intricate process and the mechanism that are required to have an excellent comprehension of the image processing the norms the ways it functions the methodology it uses the architecture so that it increases our accuracy precision and all the important features that the image processing is required and also the design so that it help us achieve our desired goal. To prioritize and make sure that after the image processing is conducted it has to eligible and have highly distinguishable features that is going to make a through comprehension for understanding the illness detection processing techniques that is done by segmentation meaning taking small chunk and then taking for the next process if the plant is affect or damaged in any way. Also, through resizing, making all the images at a certain size so that it can be much easier to detect thus increasing the efficiency and also maximizing the potentiality of the process.

To create a system that is so sophisticated that can reliably and easily identify the various kinds of citrus illnesses that might affect citrus trees. It will ensure it by using combinations of ResNet and DenseNet and later with explainable AI and then will be implemented on the sets that the model will be extremely trained and highly adaptive in detecting the disease. To evaluate the citrus diseases detection system meaning that after the models are implemented it will be able to further strengthen its ability to detect the disease that will ultimately mean that the root cause of the disease can be discovered at a faster pace.

To ensure that, after the disease is detected it can aid in initially finding the root cause of these disease which factors makes it potent and accordingly be the pioneer for farmers by providing them with sufficient information making them aware and also giving the necessary insecticides and pesticides that can eradicate the disease and relieving the farmers from the long held problems which these disease were causing and thus increasing their yield and make them more profitable in turn increasing living standards.

To improvise meaning after the disease detection will be fully functional approach many excellent suggestion can come across an then be implemented on how it is taking its course of action and thus improve like making highly accurate and assumption that can as such to even predict and which climate or season there can be a surge of certain diseases and in that way take the necessary steps that can help avert the problem as because prevention is better than cure and in these way slowly by improvise adapt overcome make a better disease model.

Chapter 3

Diseases Classification

It is basically the first step in finding the Diseases for the circus plant like Lemons, Oranges, Malta. This is a crucial phase where we must take a picture of the leaf before identifying the ailment. We require large amount of data for training. We must ensure that is acquire has to have a good resolution and distinctive. It incorporates standardization and differentiation change. For effortlessly seeing the picture must having appropriate brightness. Furthermore, differentiate the objective of this stage is to acquire a standard picture

Figure 3.1: Data sample

3.1 Citrus Black Spot

Diseased plants are sensitive to black spots on plants. The cause, along with several others, is primarily the atmosphere this represents prone to diseases such as citrus blemishes, better known as CBS. Points from Various sizes were seen, including small, oval-shaped noxious spots Gray dice, symbols of citrus leaves and fruits. Black spot infection They are dark brown in color and range in width from 0.12 to 0.4 inches. zone.

Figure 3.2: Black spot infected citrus leaves

3.1.1 Prevention

As the adage goes, prevention is preferable to treatment. The following tips for preventing citrus black spot infection, in addition to conventional best practices for citrus production, may be helpful:

• pollination in the early summer, or even sooner in the late spring, and spring pruning of the trees. In the fall, while pests are busiest, it will help stop the trees from growing leaves.

•Watering the trees is an additional choice. It's helpful to keep the trees well-watered to avoid pest infestation. Aphids and other insects are more active during dry spells and in drought-stricken areas. Therefore, it is probable that maintaining the plants well-watered will stop infection. There will almost definitely be a corresponding fall in honeydew production when the virus level decreases. Controlling the formation of honeydew considerably reduces the likelihood of a widespread fungal infection.

• The tree needs to be handled after the harvesting of the crop. To maintain the tree's health after the fruits have been harvested, a specific chemical or oil treatment can be applied. One such recommendation is imazalil oil. To stop hurting others generally, it is advised to use caution when handling such oils.

3.1.2 Treatment

The condition can be completely cured chemically with copper oxychloride Demildex.

When there is some type of weak acid present, demildex is put in water and further dissolves on the leaves. Demildex contains a variety of modes of action for the spread and development of citrus black spot. The production of honeydew is decreased because copper, and thus Demildex, is poisonous to insects. In addition, it may disintegrate in the honeydew. Demildex prevents the spread of these fungi by interfering with their reproductive process through both the honeydew vector and by coming into touch with the fungal spores directly.

3.2 Citrus Canker

Citrus canker, which affects many citrus species, is brought on by the bacteria Xanthomonas axonopodis. On the leaves, stems, and fruit of citrus trees, such as lime, orange, and grapefruit, lesions are brought on by infection. Even though it is not toxic to humans, canker has a major negative effect on the well-being of citrus trees by forcing leaves and fruit to drop off ahead of time. Fruit with a canker infection is safe to eat, but it is not suitable for marketing. The viability of American citrus has been put in jeopardy by the Asian citrus psyllid (Diaphorina citri Kuwayama, or ACP), an insect that spreads the citrus greening disease. Fruits from sick trees are sour, deformed, and green, making them unfit for commercialization as fresh or liquefied fruit.

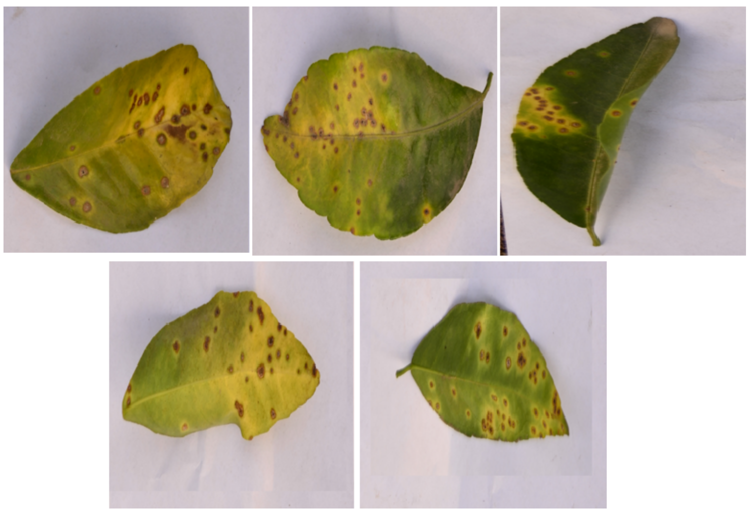

Figure 3.3: Canker infected citrus leaves

3.2.1 Prevention

As canker has no cure, It would be better if this is prevented. There are few safety measures that can be taken to prevent it.

• Keep an eye out for illness symptoms in the trees.
• Examine local laws about quarantine.
• Make sure to purchase healthy plant material through reputable sources, if at all possible.
• Adopt citrus cultivars which are more tolerant of the illness.
• In order to stop the disease from spreading, sterilize your instruments and equipment after each usage.
• To stop surrounding healthy trees from developing the disease, eradicate severely diseased trees.
• Take off any fallen branches, fruits, or leaves from the soil and trash them.

3.2.2 Treatment

When your tree is injured, whether through storm surge, pest infestations, or accidents caused while pruning, canker disease typically develops. Bacteria and fungus can easily enter and spread when there is a significant injury on the trunk. Citrus canker is incurable.

3.3 Citrus Greening

The viability of American citrus has been put in jeopardy by the Asian citrus psyllid (Diaphorina citri Kuwayama or ACP), an insect that spreads the citrus greening disease. Fruits from diseased trees are green, misshapen, and sour, rendering them unsuitable for liquid or fresh fruit marketing.

Figure 3.4: Greening infected citrus leaves

3.3.1 Prevention

• Maintain a look out for illness signs in the citrus groove on a regular basis.
• Ensure a high standard of cleanliness for citrus-growing equipment and personnel.
• Eliminate alternate psyllid hosts such Severinia buxifolia, Murraya paniculata, as well as other plants related to citrus (Rutaceae).
• Cut down any damaged trees.

3.3.2 Treatment

There is no treatment for citrus greening once it has started. The illness will eventually kill the plant because the plant will decline over time. Plants infected with citrus greening infection must be removed immediately.

3.4 Citrus Esca

Esca is said to arise from pruning wounds that weren't properly covered. It is a complicated, chronic illness where many fungi operate concurrently or one after the other to block xylem vessels, produce phytotoxic compounds and enzymes, and inflict necrosis to the vascular tissues of grapevines. Certain Vitis vinifera cultivars have higher degrees of disease resistance than others, since genotype influences stress response.

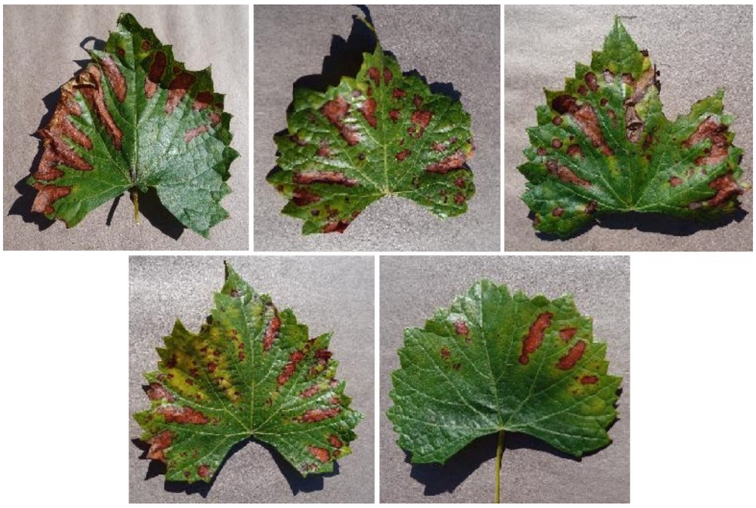

Figure 3.5: Esca infected citrus leaves

3.4.1 Prevention

• If improved crops are offered, pick those.
• Avoid moving suspect sick trees to neighboring farms or areas.
• Use of overhead irrigation is not recommended.
• Keep old limbs, branches, and fruit out of the orchard.

3.4.2 Treatment

Only protective copper sprays have been approved for use in controlling esca in citrus. As copper is a preventative fungicide, the overall fruit body must be continuously coated with copper to be shielded from microbes infection.

3.5 Citrus Healthy

Bright green leaves with finely serrated margins and a little ripple grow alternately along the branches. Additionally, the leaf has a noticeable center stem with a few minor veins.

Basically These are all the healthy leaves that can differentiate from other diseased leaves. These images are looking like natural green and shine.There will be no spot.

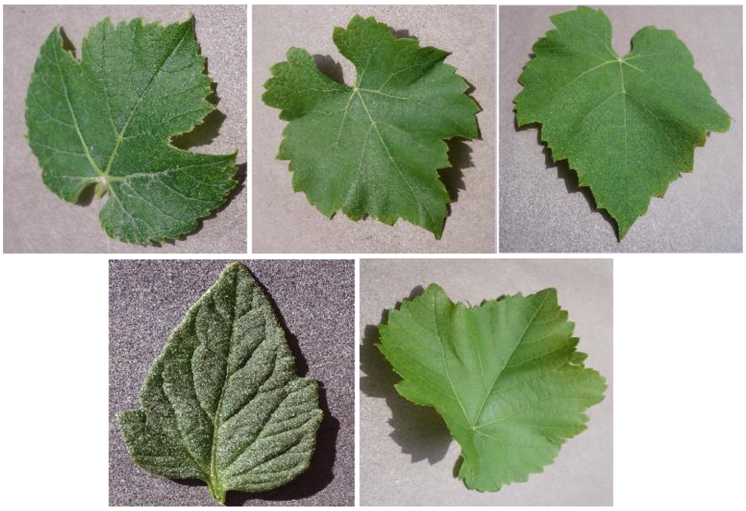

Figure 3.6: Healthy citrus leaves

Chapter 4

Implementation

4.1 Methodology

The proposed disease detection model for image processing aims to detect disease in citrus plant leaves that are collected and processed by this model. To do this, the model must develop a procedure that employs explainable AI to forecast illnesses after receiving input from images via image capture and categorization, processing the input data methodically.

Here, first of all, we acquired the necessary data did some augmentation for increasing the data and ensuring all sorts of features then processed them by removing noise, turning them into gray images finally we convert them into binary for our model to learn from them. Secondly, we split our data into there different sections some for training our few validations and lastly a few for testing our how well it works with our dataset. We used their different types of models Resnet152V2, VGG19, DenseNet. Then we compared them through Val accuracy, loss as well as the confusion matrix and finally came to the conclusion that Resnet152V2 is the best model for citrus diseases identification and so finally we made our AI application with this model for predicting citrus diseases and providing the necessary suggesstion.The model design is shown in Figure 6.1 at a high level.

The disease detection process is responsible for data collection, categorization, and prediction.

Data acquisition: Gathering and organizing the input data so that the disease detection process can handle it quickly are the main goals of this step. A technique used to artificially enlarge the data collection is called augmentation.The range of pixel intensity levels can be changed in image processing by using the normalization technique.

Data splitting: Segmenting an image using split and merge is a method of image processing.

Image Classification: This procedure groups the pictures using the VGG16, ResNet152V2, and DenseNet121 procedures, and then sends the results to Ensemble independently.

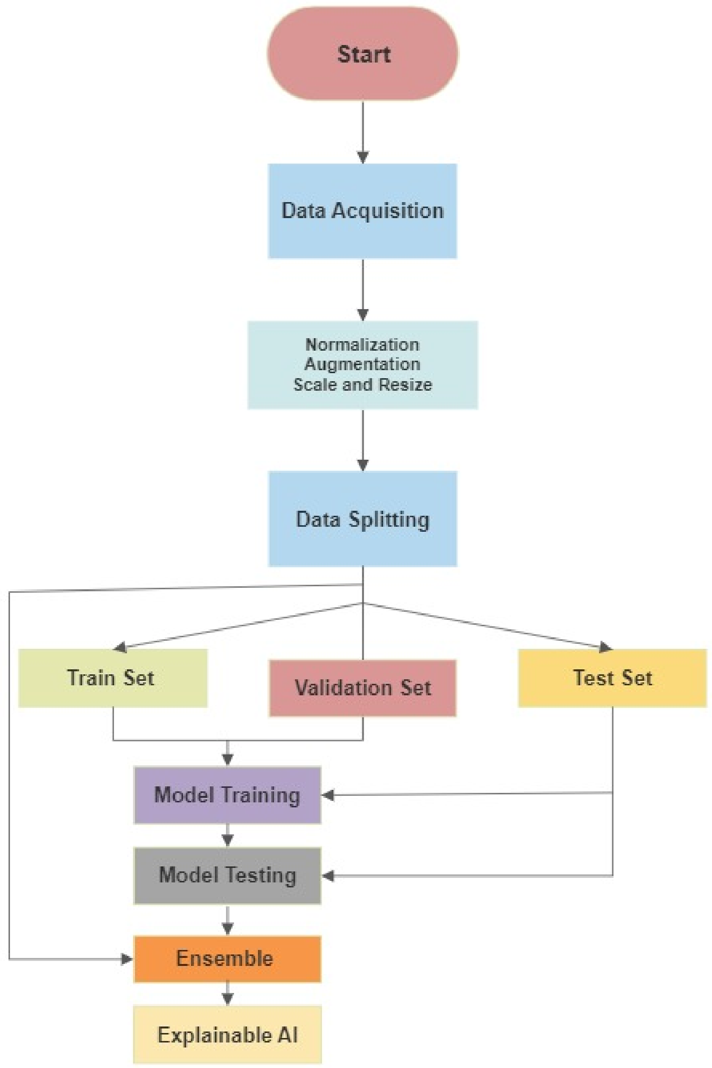

Figure 4.1: Top level architecture of the proposed disease detection model

Ensemble: This stage combines the results from different models of the previous part to give a more accurate single prediction to the Explainable AI.

Explainable AI: In order to comprehend and explain the predictions provided by machine learning models, Explainable AI provides a collection of tools and frameworks.

4.2 Data pre-processing

The data are evaluated and processed here in accordance with our specifications. The most fundamental level of abstraction is pre-processing, therefore it can be skipped if there are any significant or unneeded irregularities. It improves several photographs as well. This feature is very significant and necessary for activities involving further processing and analysis. Image enhancement and color space conversion are included. Segmentation and resizing operations can be carried out in this case such that the data has a uniform resolution regardless of the scale of the data. Segmentation is a technique used to transform a picture's representation into something that is more critical of the establishment's enthusiasm.

As a result of collecting data from the different data sets, we had to augment data of three different types of leaves by probability=0.7 with maximum left rotation=10 and maximum right rotation=10 and by zooming with probability= 0.3, minimum factor = 1.1, and maximum factor=1.6. We did this augmentation separately for Citrus Black spot, Citrus canker, and Citrus healthy leaves images.

Finally we resized all the data with an image size of 224*224. We also reduce the noises from the image by bilateralFilter we also turn the images into gray by imread for better results. Moreover, we applied applyColorMap to produce pseudocolored images.

4.2.1 Data Verifying

As our initial data was very less so we augmented the the with many pre-processing techniques like zooming,skewing , rotating(left-rotate,right-rotate), shifting(height-shift,width-shift,distortion cropping, shearing as well as mirroring to find what would the best way of augmentation for a small amount of dataset before passing to Imagedatagenarator.
In this process for case 1 we used only zooming and rotating for data augmentation and passed it to the data imagedatagenarator also with the same techniques with different value. And ultimately when we did the training the accuracy coming was very low it was underfitting.
So for case 2 we added certain more augmenting techniques with zooming and rotating like shifting and shearing and got 3500 data. Hereafter training we got the best performance of the model the model was able to predict with almost 94 percent accuracy.
For case 3 we did augmentation with certain techniques such as zooming,skewing, rotating(left-rotate,right-rotate), shifting(height-shift,width-shift, distortion cropping, shearing as well as mirroring but here we noticed a huge amount of overfitting although the model traing accuracy was very high it was not able to predict new data.
So we came to the conclusion that for a small amount dataset if we choose to do data augmentation with very simple techniques the same model gets under fitted as the same data with only slight changes is going for training. moreover, the same model gets overfitted if we choose to use a lot of augmentation techniques. So we can say its ideal to use only a few augmented techniques rather like zooming , rotating , shearing not a the techniques which makes the learning for the model complex.

Table 4.1: Data verifying table

Case no	Data	Accuracy	Problem
Case 1	2500	67%	Underfitting
Case 2	3500	94%	Normal(almost)
Case 3	5000	99.5%	Overfitting

4.3 Data splitting

We collected the data from different sources but all of them are very few in terms of numbers. So, it is a very big challenge to manipulate an appropriate data set for our work. We merged a few of them to get a standard size for work.

Firstly from the dataset we kept aside almost 5 percent data.Moreover we also added some data from google raw images and then For training, and validation, data was divided in the proportion of 80:20.
The Table for training testing and validation of different classes is given below:

Table 4.2: Data classification table

Class name	Training	Validation
Citrus Black Spot	469	118
Citrus Esca	605	151
Citrus Canker	440	109
Citrus Greening	633	159
Citrus Healthy	653	163
Total	2800	700

4.3.1 Citrus leaves Grayscale and RGB

By using the cv2.IMREAD_GRAYSCALE method we converted the images to grayscale for our 1st implementation step and then for the second Implementation step we used cv2.IMREAD_UNCHANGED method to read the transparency channel along with the color channels of the images.Moreover, we turned the images into pseudocolor images,removed noises with bilateralFilter method for making the model training much more smooth.Lastly We also resized the images to 224*224.

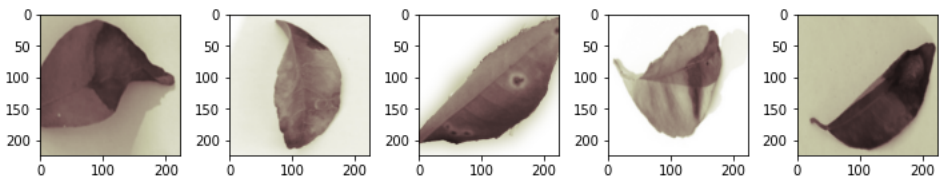

Figure 4.2: Processed data sample1

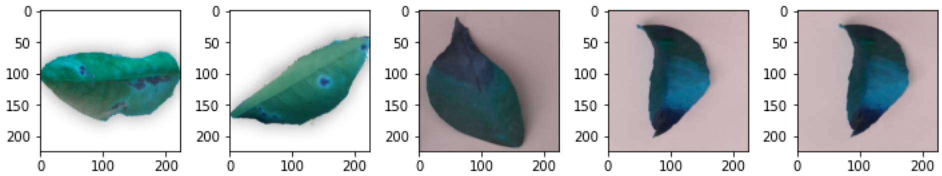

Figure 4.3: Processed data sample2

4.4 Proposed Models

Different steps were utilized to train our model. First, we trained with all of the classes using ResNet152V2, DenseNet121, and VGG19 in the first stage.
Then, in the second stage, we eliminated the diseases that performed the best and retrained using Resnet50, DenseNet121, and Resnet101 with the diseases that did not do well. Although the testing and validation accuracy for these classes in the first stage was good, the testing accuracy was not that high because the model was slightly overfitting because we were using grayscale images. As a result, the model was unable to distinguish between these three classes in this situation because it had a lot to learn. As a result, with all the classes present at once, it was becoming complicated.

We trained the model using RGB color photos and only three diseases because the learning process for the model with fewer classes was a little simpler. Therefore, it was easy to distinguish them from one another. Learning complexity and rate both dropped as a result. Additionally, because the feature was present, RGB color representations explicitly demonstrated the differences between the classes. We took

this action because the model was having issues with the other two classes if we had used grayscale photos for all classes. On the other hand, the model did not do as well with the remaining three classes when using RGB-clored images.

In addition, the model performs well in comparison when the learning complexity is reduced. The outcomes are displayed following the architecture.

The model we used for our thesis are given below

4.4.1 Model VGG19

Convolution and Max Pooling layers are the building blocks of the Visual Geometry Group, or VGG. There are two versions, VGG16 and VGG19, each having 16 or 19 layers. CNN is better able to perform more complicated tasks as the number of layers rises. Using the ImageNet database, which has one million photos divided into 1000 categories, the VGG19 algorithm is trained. As each convolutional layer uses multiple 3 3 filters, it is a particularly well-liked technique for detecting pictures. The Basically VGG19 model, a variation of the VGG model, has 19 layers (16 convolution layers, 5 MaxPool layers and, 3 Fully connected layer and 1 SoftMax layer).

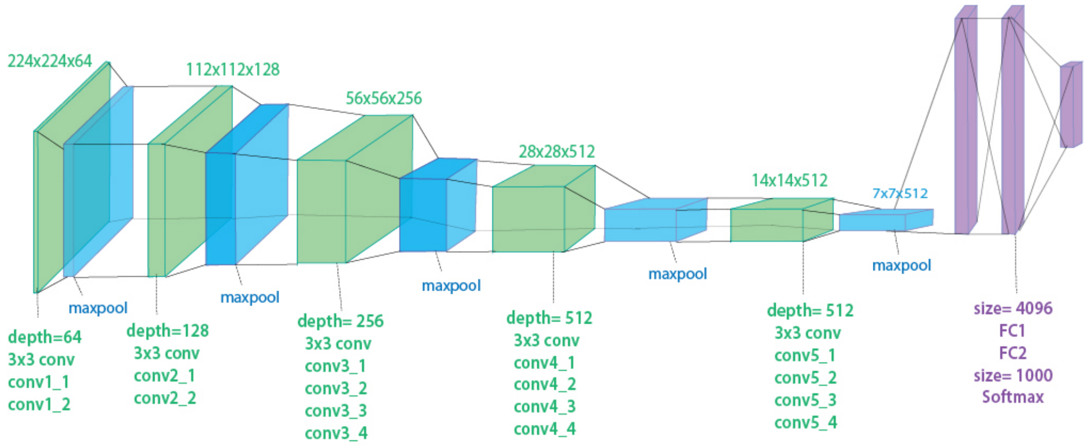

Figure 4.4: VGG19 architecture diagram

4.4.1.1 Architecture

•A fixed-size (224 * 224) RGB image was provided as input to this network, suggesting that the matrix was formed (224,224,3).It was added to each pixel after being applied over the full training set.
• utilized kernels with a stride size of 1 pixel and a size of (3 * 3), encompassing the complete picture.
• Spatial padding was utilized to preserve the image's spatial resolution. With Sride 2, max pooling over a 2 by 2 pixel window was made possible.
•The Rectified Linear Unit (ReLu), which added non-linearity to the model to enhance classification and speed up calculation, was introduced after this. Then, to increase classification accuracy and calculation speed, rectified linear unit (ReLu) was employed to introduce non-linearity to the model. This model outperformed prior models based on tanh or sigmoid functions by a large margin.
• Three completely linked layers were put into place, the first two of which had a 4096 size. The layer with 1000 channels for 1000-way ILSVRC classification is followed by a layer with a softmax function as the third layer.

4.4.2 Model DenseNet121

One of the models in the DenseNet family created for picture classification is the densenet-121 model. By using shorter links between the layers, the DenseNet architecture seeks to increase both the depth and training effectiveness of deep learning networks. Every layer is connected to every layer underneath it by a deep neural network termed DenseNet. The very first layer is connected to the second, third, fourth, and so on layers, whereas the second layer links to the third, fourth, fifth, and so forth levels.

4.4.2.1 Architecture

As seen, each dense block has a distinct number of layers (repetition) with two convolutions, a bottleneck layer with a 1x1 kernel size and a convolution layer with a 3x3 kernel size. •Basic pooling layer with 3x3 max pooling and a stride of 2 and 64

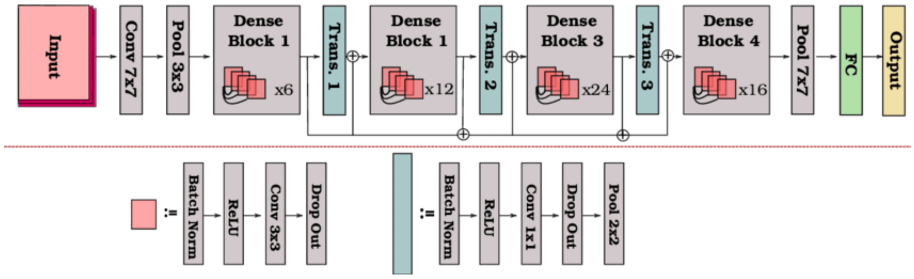

Figure 4.5: DenseNet121 architecture diagram

7X7 size filters for the basic convolution layer.
• Six times each, two convolutions appear in Dense Block
• Transition's first layer (1 AvgPool + 1 Conv)
• Transition layer 2 (1 Conv + 1 AvgPool) and Dense Block 2 (2 Convs, 12 Repetition)
•Transition layer 3 (with 1 Conv and 1 AvgPool) and Dense Block 3 (2 convolutions, repeated 24 times each)
•16 repetitions of dense Block 4 with 2 convolutions
• 16 repetitions of dense Block 4 with 2 convolutions
•Final layer

4.4.3 Model Resnet50

ResNet-50 is a convolutional neural network with 50 layers. A variety of computer vision algorithms are supported by the ResNet neural network, which refers for Residual Networks. ResNet's main innovation was our capacity to train very sophisticated neural networks with far more than 150 layers. One MaxPool layer, 48 convolutional layers and one average pool layer make up the 50 layers.

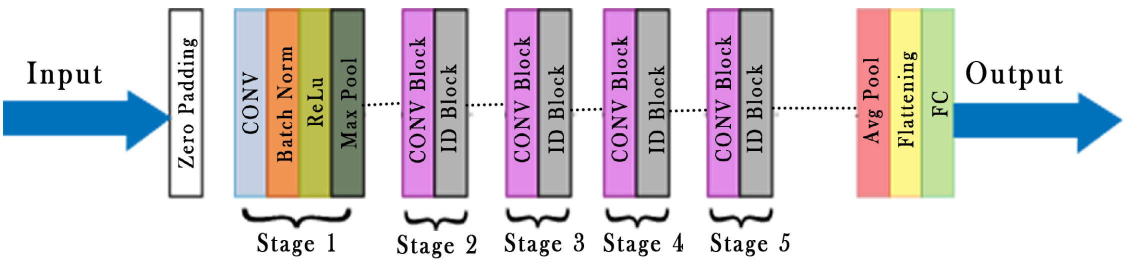

Figure 4.6: Resnet50 architecture diagram

4.4.3.1 Architecture

A convolution with a kernel size of 7 * 7 and 64 different kernels, each with a stride size of 2, is used to create one layer. The following illustration uses max pooling and a stride size of 2. The 3 * 3,64 kernel comes after the 1 * 1,64 kernel, and the last kernel is the 1 * 1,256 kernel. We have nine levels in this stage thanks to the three times that these three layers are repeated. We then see a kernel of 1 * 1,128 followed by a kernel of 3 * 3,128 and a kernel of 1 * 1,512 as the last kernel. Four times through this process, a total of 12 layers were added. The next kernel is of size 1 * 1,256, while the following two kernels are of size 3 * 3,256 and 1 * 1,1024; There are six times this repeated, offering together a total of 18 layers. Then came two more kernels of 3 * 3,512 and 1 * 1,2048, and finally a 1 * 1,512 kernel. We repeated this procedure three times for a total of nine layers. Then, we do an average pool, complete it with a layer that is entirely linked and has 1000 nodes, and last, we add a softmax function to create one layer. In reality, neither the maximum/average pooling layers nor the activation actions are actually counted.

4.4.4 Model Resnet152V2

Layer skipping is possible in the artificial neural network Resnet 152 V2 Residual Network (ResNet) architecture without sacrificing performance. You should be aware of the following. Resnet includes a component known as a residual learning unit to stop deep neural networks from deteriorating. This unit's feedforward network structure adds new inputs to the network and generates new outputs via a shortcut link. This unit's key advantage is that it improves classification accuracy without making the model more complex. We make use of Resnet152V2, which is the Resnet family member that is the most accurate.

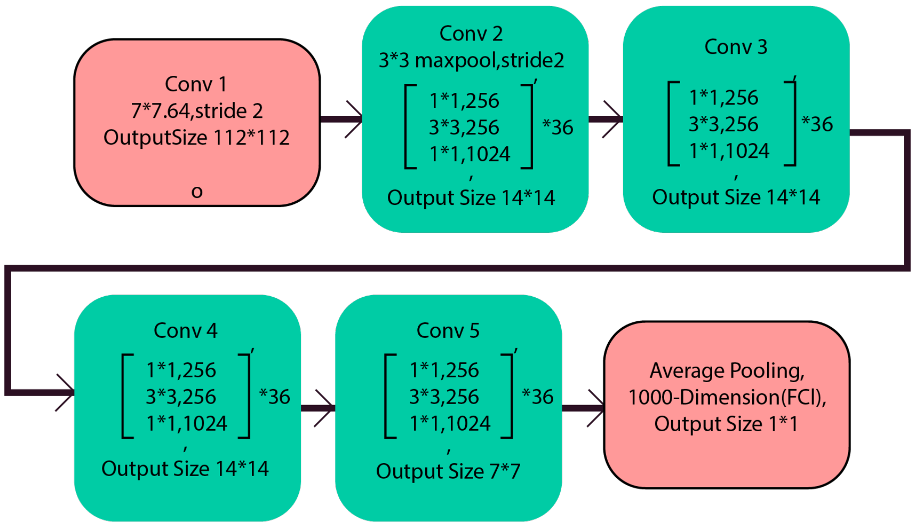

Figure 4.7: ResNet152V2 architecture diagram

4.4.4.1 Architecture

• The highest completely linked layer of the network should be added, whether or not it is. Weights might be None (random initialization), "imagenet" (pre-training for imagenet), or the location to the weights file that has to be imported. Tensor input option Layers' outcome, often known as the keras tensor Use Input to provide the model image data ().
• The input shape must be (224, 224, 3) (with "channels last" data format) or (3, 224, 224) and may only be provided if include top is False (with "channels first" data format). It should have exactly 3 input channels and a maximum width and height of 32. One appropriate number would be (200,200,3).
• Combining A possible pooling method for feature extraction exists when include top is set to False. The last convolutional block's 4D tensor will be the model's output.Avg indicates that the final convolutional block's output will be converted into a 2D tensor using global average pooling.MAX indicates that global max pooling is being used.
• When the weights argument is absent and the includes top argument is True, classes—the maximum number of classes that can be used to group photos—must be supplied.
• The classifier is turned on via a callable or str. The "top" layer should be activated using this function. In the absence of include top being set to True, it is ignored. To restore the "top" layer's logics, set classifier activation= None. Only "softmax" or None are acceptable classifier activations for pre-trained weights.

4.4.5 Ensemble model

Ensemble modeling is the process of creating multiple diverse models to predict an outcome using a range of modeling algorithms or training data sets. The ensemble model then incorporates the forecast from each base model to create a final, unified forecast for the unobserved data. Using ensemble models aims to reduce the generalization error of the prediction. When the base models are varied and independent, the ensemble method eliminates the model's prediction error. To produce a forecast, the strategy appeals to the wisdom of the crowd. Even when it has a large number of base models, the ensemble model acts and performs as a single model. For our final prediction, we constructed an efficient ensemble model where we combined the best two models of the two different classes for predicting our diseases. We implemented a new algorithm for the ensemble based on disease priority. This ensemble technique has provided us the opportunity of training the model less number of classes in every stage.
The Pseudocode is given below:

```
#Program start
.       Start
#Input section
.       load the image with target size 224*224
#Processing section
.       convert test image to np array and normalize
.       change the dimension 3D to 4D
.       Run Resnet152V2
.       get the index of the max value
.           if pred=1
.               print("Citrus Esca)
.           else if pred = 0 or pred = 2 or pred = 3
.               Run DenseNet121
.               if pred=0 ;print("Citrus Blackspot")
.               else if pred=2 ;print("Citrus Canker")
.               else if pred=3 ;print("Citrus Greening")
.           else: print("Citrus Healthy")
#Program end
.       End
```

4.5 Result and Analysis

4.5.1 Implementation Method 1

4.5.1.1 ResNet50

The performance of ResNet50 for our working dataset is very low margin as the leaves distinguishing feature are not high so for a simple model in which the learning rate is very shallow as well as adaptability with different images.As a result, the error rate is very high

Accuracy and Loss

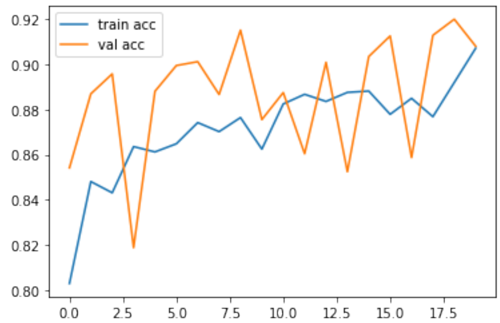

Figure 4.8: Accuracy

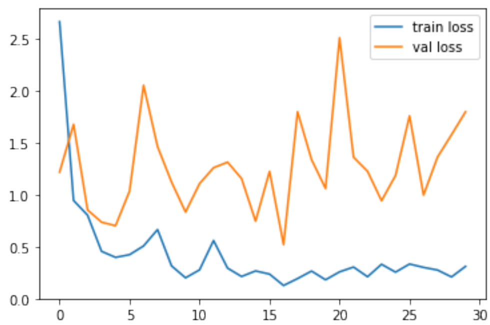

Figure 4.9: Loss

Precision, Recall, F1-Score,Support

4/4 [==============================] - 2s 247ms/step

	precision	recall	f1-score	support
0	0.30	0.75	0.43	16
1	0.96	1.00	0.98	27
2	0.80	0.19	0.31	21
3	0.65	0.62	0.63	21
4	0.80	0.52	0.63	23
accuracy			0.63	108
macro avg	0.70	0.62	0.60	108
weighted avg	0.74	0.63	0.63	108

Figure 4.10: Classification report-ResNet50

Confusion Matrix

The performance of a classification system is presented in a confusion matrix table. A confusion matrix displays and summarizes the results of a classification process.

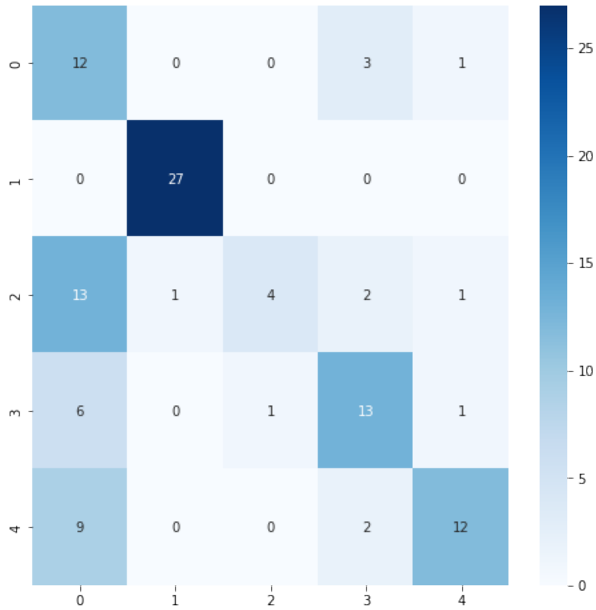

Figure 4.11: Confusion Matrix

In the above confusion matrix, there are 5 classes and 5 rows each of them is 'citrus black spot, citrus canker, Citrus greening, citrus healthy and Citrus esca respectively. Moreover, we can see the model is accurately identifying Citrus Esca but has a huge problem in the case of all other diseases.

4.5.1.2 ResNet152V2

Accuracy and Loss

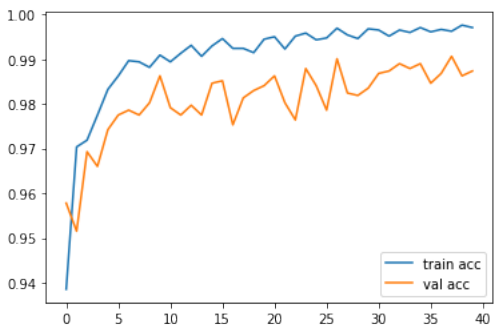

Figure 4.12: Accuracy

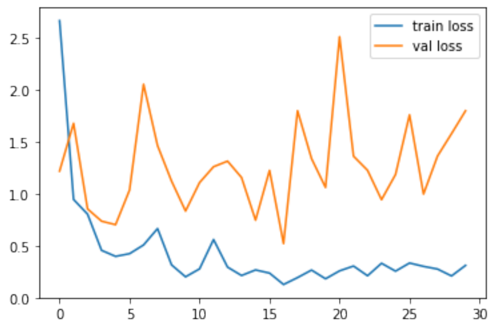

Figure 4.13: Loss

Precision, Recall, F1-Score,Support

```
4/4 [==============================] - 5s 376ms/step
              precision    recall  f1-score   support

           0       0.86      0.75      0.80        16
           1       1.00      1.00      1.00        27
           2       0.88      1.00      0.93        21
           3       0.86      0.90      0.88        21
           4       1.00      0.91      0.95        22

    accuracy                           0.93       107
   macro avg       0.92      0.91      0.91       107
weighted avg       0.93      0.93      0.92       107
```

Figure 4.14: Classification report-resnet152V2

Confusion Matrix

The outcomes of a classification algorithm are displayed and summarized in a confusion matrix. This article presents the confusion matrix for the ideal system. This graph makes the pattern of the observed data more obvious by using different colors to depict the various matrix values. All of the values in the row are typical. To list the information in each square, we match the colors. Classifying photos can be done with a low error rate. Particularly for the classes of citrus healthy and citrus greening, our validation accuracy was very good. We did remarkably well in classifying citrus canker and citrus black spot. In the sections that follow, we'll go through our experimental results in much more depth and make comparisons.

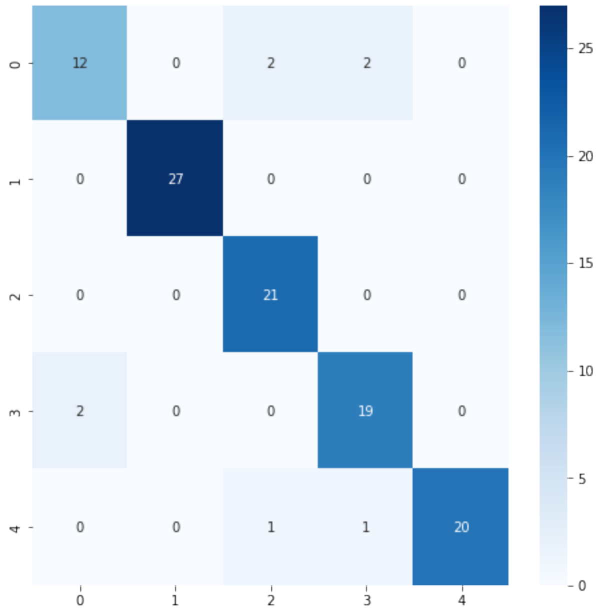

Figure 4.15: Confusion Matrix

In the above confusion matrix, there is 5 classes and 5 rows each of them is 'citrus black spot', 'citrus canker', 'citrus greening', 'citrus healthy', and 'citrus esca' respectively.Moreover, we can see the model the model is accurately identifying 100 images but confuses 8.

4.5.1.3 Densenet121

The performance of the Densenet121 is significantly good. The overfitting and underfitting rate have decreased noticeably. **Accuracy and Loss**

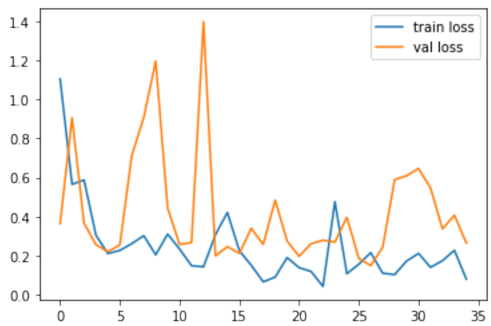

Figure 4.16: loss

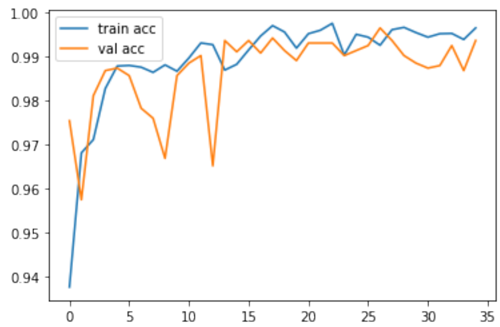

Figure 4.17: accuracy

Precision, Recall, F1-Score,Support

```
2/2 [==============================] - 5s 1s/step
              precision    recall  f1-score   support

           0       0.92      1.00      0.96        11
           1       0.95      1.00      0.97        18
           2       1.00      0.87      0.93        15

    accuracy                           0.95        44
   macro avg       0.95      0.96      0.95        44
weighted avg       0.96      0.95      0.95        44
```

Figure 4.18: Classification report-DenseNet121

Confusion Matrix

The confusion matrix for the best system is presented in this work. this graph displays the various matrix values with various colors, which makes the observed data pattern clearer.

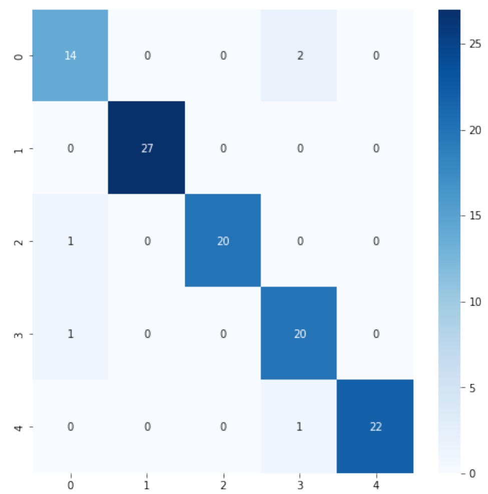

Figure 4.19: Confusion Matrix

4.5.2 Implementation Method 2

4.5.2.1 ResNet101

As ResNet101 is a little bit simple model comparatively its performance was below our expected result.

Accuracy and Loss

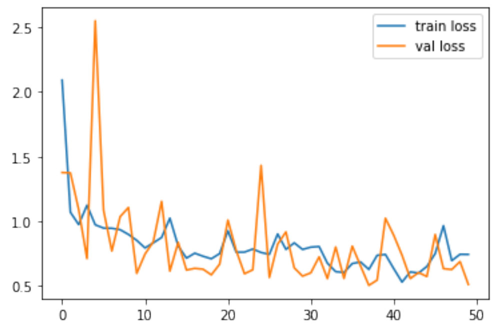

Figure 4.20: loss

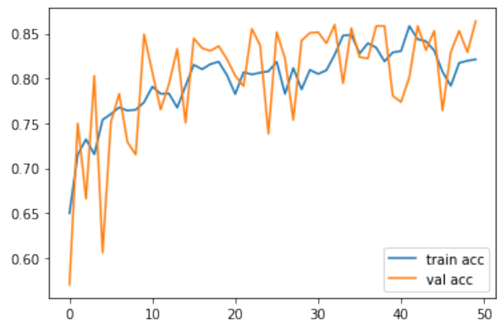

Figure 4.21: accuracy

Precision, Recall, F1-Score,Support
As the rest of the leaves' features are quite complex so when we used comparatively a simple model for two classes the false positive and false negative increased significantly.

2/2 [==============================] - 2s 170ms/step

	precision	recall	f1-score	support
0	0.47	0.64	0.54	11
1	0.69	0.61	0.65	18
2	0.62	0.53	0.57	15
accuracy			0.59	44
macro avg	0.59	0.59	0.59	44
weighted avg	0.61	0.59	0.59	44

Figure 4.22: Classification report-resnet101

Confusion Matrix

The confusion matrix for the best system is presented in this work. this graph displays the various matrix values with various colors, which makes the observed data pattern clearer. The values in the row are all standard. We match the colors and list the data in each square. A very high mistake rate can be seen while classifying images. Because the model couldn't extract the features accurately. Though training accuracy was good overall accuracy was below average. In the above confusion

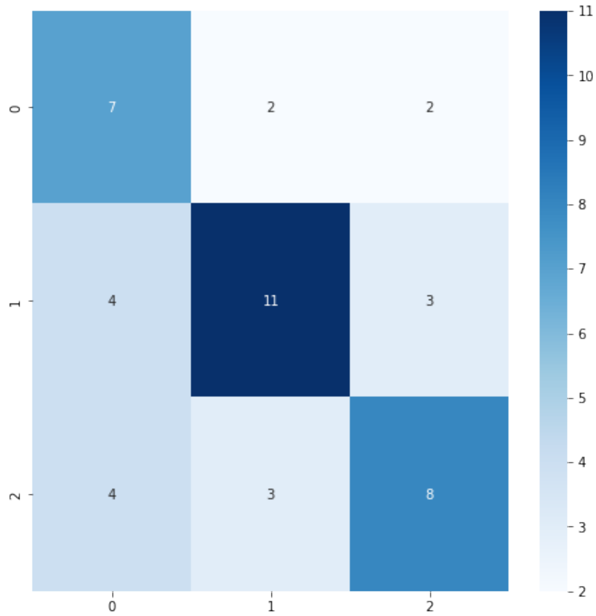

Figure 4.23: Confusion Matrix

matrix, there are 3 classes and 3 rows each of them is citrus black spot, citrus greening and citrus canker respectively. Moreover, we can see the model is accurately identifies 26 images but confusing with 18 leaves.

4.5.2.2 DenseNet121

In this, we were able to identify all the images accurately with an accuracy rate of 95 percent in each class. the loss also minimized a lot.

Accuracy and Loss

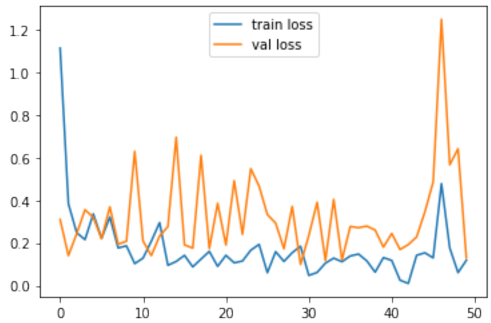

Figure 4.24: loss

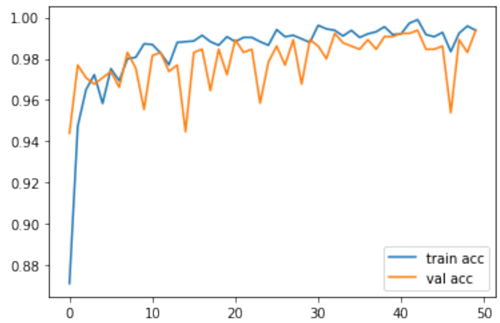

Figure 4.25: accuracy

Precision, Recall, F1-Score,Support

```
2/2 [==============================] - 5s 1s/step
              precision    recall  f1-score   support

           0       0.92      1.00      0.96        11
           1       0.95      1.00      0.97        18
           2       1.00      0.87      0.93        15

    accuracy                           0.95        44
   macro avg       0.95      0.96      0.95        44
weighted avg       0.96      0.95      0.95        44
```

Figure 4.26: Classification report-DenseNet121

Confusion Matrix

This article presents the confusion matrix for the ideal system. This graph makes the pattern of the observed data more obvious by using different colors to depict the various matrix values. All of the values in the row are typical. To list the information in each square, we match the colors. Classifying photos can be done with a low error rate. All three classes showed extremely good validation accuracy. Citrus black spot and citrus canker are categorized diseases, we performed significantly. Here is 3

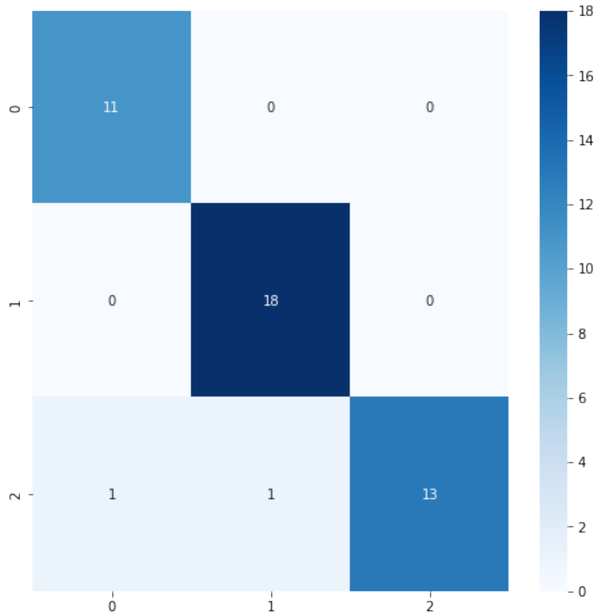

Figure 4.27: Confusion Matrix

classes and 3 rows each of them is 'citrus black spot', citrus canker,a citrus greening, respectively. Moreover, we can see the model accurately identifying 32 images but confusing 2 of Citrus Greening Citrus Canker is giving no false positive.

4.5.2.3 VGG19

The output of the classification algorithm is shown and summarized in a confusion matrix. In a confusion matrix, the results of a classification algorithm are shown and condensed.

Accuracy and Loss

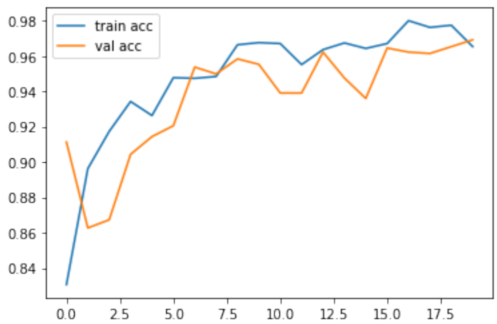

Figure 4.28: Accuracy

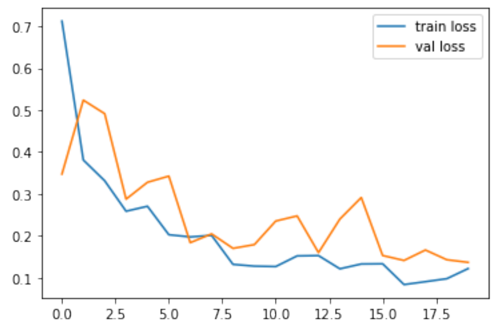

Figure 4.29: Loss

Precision, Recall, F1-Score,Support

```
2/2 [==============================] - 4s 1s/step
              precision    recall  f1-score   support

           0       0.73      0.73      0.73        11
           1       1.00      0.83      0.91        18
           2       0.83      1.00      0.91        15

    accuracy                           0.86        44
   macro avg       0.85      0.85      0.85        44
weighted avg       0.88      0.86      0.86        44
```

Figure 4.30: Classification report-VGG19

Confusion Matrix

In this study, the confusion matrix for the ideal system is described. The pattern of the observed data is made apparent by this graph, which uses different colors to indicate different matrix values. Each value in the row is typical. We match the colors, then enter the information in each square. When classifying images, a low error rate can be attained. For the citrus healthy and citrus greening classes, our validation accuracy was quite good. We did well in categorizing citrus canker and citrus Greening. In the above confusion matrix, there is 5 classes and 5 rows each

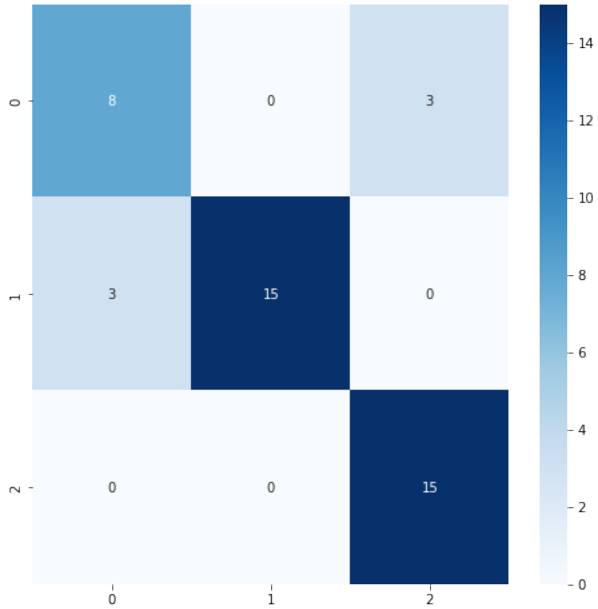

Figure 4.31: Confusion Matrix

of them is citrus black spot, citrus greening, citrus canker, citrus healthy and citrus esca respectively. Moreover, we can see the model the model is accurately identifying 100 images but confusing 20 Citrus Black spot images to Citrus Canker,21 to Citrus greening and 3 with Citrus Healthy leaves.

4.5.3 For All Classes Acquired Results

ResNet50, ResNet152V2, and VGG16 were the three models we used to train for five different illness classes simultaneously. And from here, we can see that despite using a relatively simple model, we were unable to achieve high quality performance from model training. To make matters worse, only 45% of the data we concluded the testing with the model were successfully predicted, and there was a significant amount of overfitting. Additionally, validation accuracy was very poor.Then, as part of our plan, we decided to use a complex model and feed our data into it. For this, we selected ResNet152V2, which has a lot more convolutional layers than resnet50 and was able to achieve testing accuracy of almost 86 percent. Despite some overfitting issues, however, this model still performed well because we addressed these issues in our second implementation part. Additionally, we trained our model using VGG19, whose testing accuracy is just marginally less than ResNet152V2's at 82 percent. Since ResNet152V2 uses only 240M FLOPs and minimizes the number of rows and columns by a factor of 2, it was ultimately chosen for the first stage of prediction. The following max pooling procedure also applies a factor of 2 reductions. On the other hand, the VGG19's four fully connected layers generate about 10B FLOPs.

Table 4.3: Result For All Classes Table

Model	Train Accuracy	Validation Accuracy	Test Accuracy
Resnet50	80%	63.7%	45%
Resnet152V2	98.1%	95%	86%
VGG16	98.9%	96.2%	82%

4.5.4 For 3 Classes Acquired Results

As the classes have been shrunk, we can see that every model is operating a lot more effectively. Additionally, there was barely any overfitting in this area. We chose DensNet121 from among the three top-performing models since it performed the best overall.

Table 4.4: Result for Three Classes Table

Model	Train Accuracy	Validation Accuracy	Test Accuracy
Resnet152V2	98%	95%	90%
DenseNet121	98%	96%	91.7%
VGG16	92%	90%	87%

4.5.5 Explainable AI

After building and training the model,By using Lime we decided to display the traits and regions of the leaves based on which our model is identifying the appropriate diseases.LIME (Local Interpretable Model-agnostic Explanations), an explainable AI technique, aids in illuminating a machine learning model and making each prediction's particular implications understandable. The technique is appropriate for local explanations since it describes the classifier for a particular single instance.

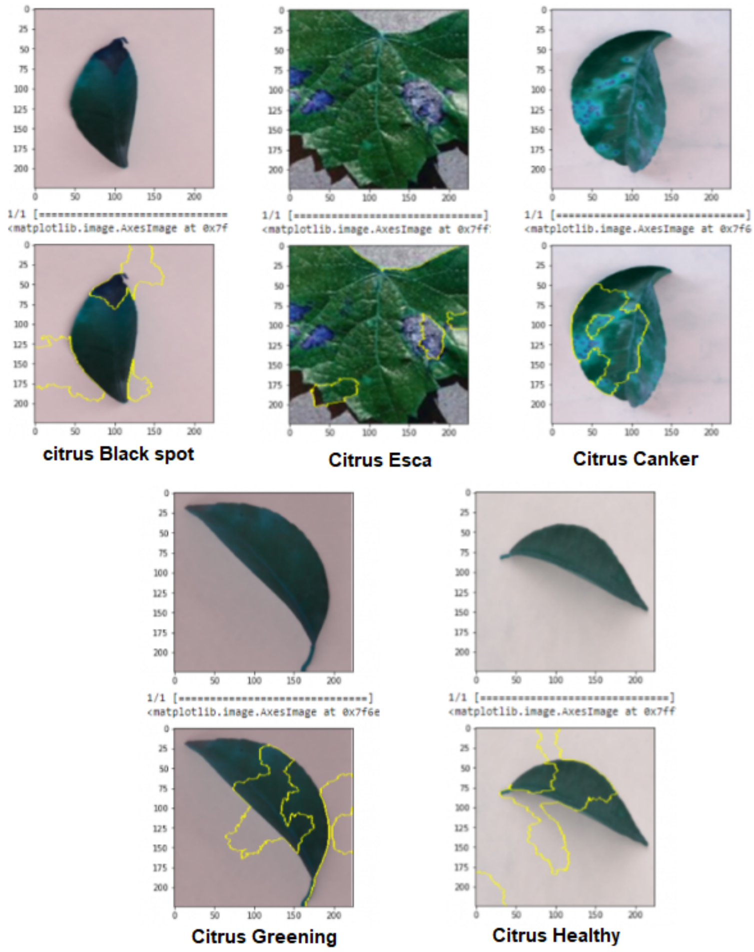

Figure 4.32: AI Demo

4.5.6 AI Demo

Finally, after Finishing our model, we put it into practice using Python'smachine-learningg language and made it functional with HTML and CSS. We constructed a website that will be providing farmers with a huge helping hand in citrus disease treatment.Additionally, our website will also provide the necessary knowledge for increasing the growth of citrus plants.

Figure 4.33: AI Home Page

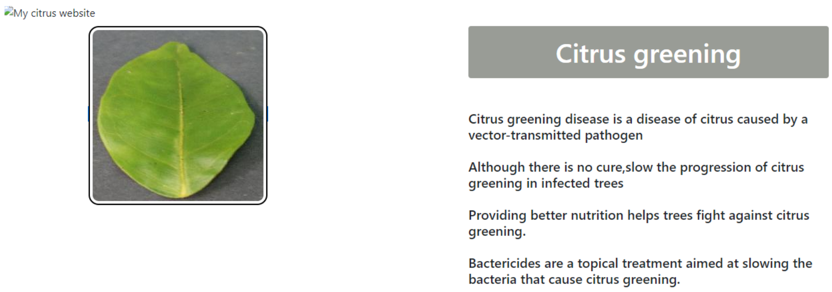

Figure 4.34: Image predicting page

Chapter 5

Conclusion

Through extensive research and survey we have deduced that the detection of the citrus disease is extremely important as it a crucial part for our ecological system. Our research addresses the challenges and the grave importance and try to figure out a definitive technique in how to incorporate in AI that can be of aid disease detection. Here from the given information acquired we have seen identified research in this area or segment is paid less attention. There are a lot of factors that are held accountable. Firstly, comes the cost whether any process that is to successful it must be cost effective along with being efficient then comes the geographical climatic and nutritional disorders meaning the variations makes many permutation making it hard for more accuracy. According to each disease's characteristics and scope of afflicted areas, the threshold value varies. Another major barrier is the availability of.Processes like preprocessing, feature extraction, segmentation, and classification get easier when we have access to a large amount of data. Since there is a lot of training data, each stage may be compared to its technique, effectiveness, strength, and weakness. So as a result the algorithms that would have highly efficient is yet to be proclaimed. Thus this research was conduct in an attempt to comprehend the detection so give remedy or at least help to deplete and find out the root cause of the disease so that it can be eradicated. With our work we hope to narrow down in finding the common diseases. With sheer perseverance we hope to accomplish our goal and not only that and also we all be able to help our fellow farmers who suffer from these disease.

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