A Project Report On

CITRUS FRUITS AND LEAVES DISEASES DETECTION USING DEEP NEURAL NETWORK MODEL

Submitted in partial fulfillment of the requirement for the 8^{th} semester

Bachelor of Engineering

in

Computer Science and Engineering

DAYANANDA SAGAR COLLEGE OF ENGINEERING

(An Autonomous Institute affiliated to VTU, Belagavi, Approved by AICTE & ISO 9001:2008 Certified)

Accredited by National Assessment & Accreditation Council (NAAC) with 'A' grade

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Coguide - Industry

2022 - 2023

Department of Computer Science and Engineering

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CERTIFICATE

This is to certify that the project entitled **Citrus Fruits and Leaves Diseases Detection using Deep Neural Network Model** is a bonafide work carried out by **Aditi Anand Huralikoppi** [**1DS19CS010**], **Guduru Rama Koushika** [**1DS19CS054**], **Koppala Jyoshna** [**1DS19CS072**] and **Kunche Nithya Sree Royal** [**1DS19CS075**] in partial fulfillment of 8th semester, Bachelor of Engineering in Computer Science and Engineering under Visvesvaraya Technological University, Belgaum during the year 2022-23.

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1..........................	....
2............................	....

Acknowledgement

We are pleased to have successfully completed the project **Citrus Fruits and Leaves Diseases Detection using Deep Neural Network Model**. We thoroughly enjoyed the process of working on this project and gained a lot of knowledge doing so.

We would like to take this opportunity to express our gratitude to **Dr.B G Prasad**, Principal of DSCE, for permitting us to utilize all the necessary facilities of the institution.

We also thank our respected Vice Principal, HOD of Computer Science & Engineering, DSCE, Bangalore, **Dr.Ramesh Babu D R**, for his support and encouragement throughout the process.

We are immensely grateful to our respected and learned guide, **Dr.C Vinothini**, Associate Professor CSE, DSCE and our co-guide **Mr Nirmal Kumar**,Alumini, DSCE for their valuable help and guidance. We are indebted to them for their invaluable guidance throughout the process and their useful inputs at all stages of the process.

We also thank all the faculty and support staff of Department of Computer Science, DSCE. Without their support over the years, this work would not have been possible.

Lastly, we would like to express our deep appreciation towards our classmates and our family for providing us with constant moral support and encouragement. They have stood by us in the most difficult of times.

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Citrus Fruits and Leaves Diseases Detection using Deep Neural Network Model

June 6, 2023

Abstract

Diseases that affect citrus fruits and leaves are the main reason for the loss in citrus fruit production in agriculture. Oranges and lemons, despite being two crops with substantial commercial value, are nevertheless susceptible to several illnesses that can result in severe yield losses. The primary cause of the drastic drop in citrus fruit yield is citrus fruit diseases and thus have an impact on the food supply, lower agricultural production and yield. There are thus huge financial losses. Citrus is an agricultural product that has substantial economic significance on a global scale. A variety of illnesses and pests, however, seriously impair citrus production. As a result, there are significant yield and quality losses in citrus production. The suggested CNN model aims to distinguish between fruit and leaf types that are healthy and those that have common citrus illnesses like black spot, canker, scab, greening, and Melanose. By combining multiple layers, the proposed CNN model captures complementing discriminative characteristics. On the Citrus and PlantVillage datasets, the CNN model was compared to other cutting-edge deep learning methods. Citrus fruit illnesses dataset used in this work is 1478 photos in size, which is a restriction in the proposed method. Utilising deep learning techniques to create an automated detection system using a convolutional neural network allows for the early diagnosis of diseases. By mixing and fusing numerous layers, the diseased citrus fruits and leaves of Canker, Greening, Melanose, Black Spot, and Scab are distinguished from the healthy leaves. The major goal of our suggested approach is to create a model that recognises the condition and assigns the appropriate disease class to the image.While machine learning classifiers use traditional feature representation techniques to categorise images, deep learning classifiers use a high number of layers with an ideal parameter set. With a test accuracy of 94.55 percent, the CNN Model is a useful tool for farmers who want to categorise citrus fruit/leaf illnesses.

Contents

1 Chapter 1

1.1 Introduction

Oranges, lemons, and grapefruits are just a few examples of the citrus fruits that are prized as crops around the world for their dietary and commercial value. The quality and quantity of the fruit produced by citrus trees can, however, be greatly impacted by a number of diseases and pests. For effective disease control and the avoidance of crop losses, early disease diagnosis is essential.Machine learning methods, in particular Convolutional Neural Networks (CNNs), have become effective tools for spotting plant illnesses in recent years. CNNs have demonstrated to be quite proficient at classifying images, including identifying and diagnosing plant diseases. Researchers and farmers can create automated systems for the rapid and precise detection of citrus fruit and leaf diseases by utilising the capabilities of CNNs.

2 The Problem

Finding citrus diseases poses a number of difficulties for farmers. These are some of the main issues they run into:

Lack of knowledge: Citrus diseases require specialised knowledge and experience to recognise and diagnose. It's possible that many farmers lack the necessary education or experience to identify plant pathogens or diseases. This lack of knowledge can result in delayed or incorrect disease detection, which can affect the timing of therapies and the management of diseases.

Visual Similarity of Symptoms: Different citrus diseases might present with symptoms that are visually similar, making it difficult to differentiate between them based purely on visual inspection. Various illnesses can share symptoms like leaf discoloration, wilting, or malformed fruit, or they may even resemble non-disease factors like nutrient deficits or environmental stress. Due to the similarities of the symptoms, diseases may be misdiagnosed and misinterpreted.

Early-stage detection: Early disease detection is essential for successful disease management in the citrus industry. Some illnesses, however, did not exhibit any symptoms in the initial stages of infection, making it challenging to diagnose them. It may already be too late to control and lessen the effects of the disease by the time symptoms start to appear.

Large-scale monitoring: Due to the size of citrus orchards, it is not practicable for farmers to visually verify each tree or plant. Manual citrus tree health monitoring is time-consuming, labour-intensive, and might not be practical for extensive commercial operations.

Due to this restriction, proactive disease management strategies may be hindered and disease detection may be delayed.

Awareness and Education: Lack of awareness can lead to negligence in implementing preventive measures or seeking professional assistance for disease detection. To address these problems, efforts should be made to provide training and educational programs to farmers, promoting disease awareness and early detection techniques. Access to affordable diagnostic tools and resources, such as portable diagnostic kits or digital platforms for remote diagnosis, can also aid farmers in accurate disease identification. Additionally, the development of user-friendly and cost-effective technologies, such as mobile applications or handheld devices, can empower farmers to detect and monitor citrus diseases more effectively on their farms.

2.1 Real World Applications

The creation and use of automated disease detection systems utilizing computer vision and machine learning technologies is one of the real-world applications of citrus disease detection. These technologies employ a number of methodologies to swiftly and precisely identify and diagnose citrus illnesses.Here are a few noteworthy examples:

Imaging-based disease detection: Images of citrus trees and fruits are taken using digital imaging technology, such as high-resolution cameras or drones fitted with multispectral or hyperspectral sensors. Computer vision techniques are then used to process these photos in order to find illness patterns and symptoms. In order to categorise and detect diseases, machine learning models, particularly CNNs, are trained on massive datasets of labelled images. This enables quick and non-destructive detection.

Smartphone applications for disease diagnosis: Mobile apps have been created to give citrus producers instant disease detection. These applications make use of the smartphone's camera to take pictures of infected citrus trees or fruits. Machine learning algorithms built into the app analyse the photographs to identify disease symptoms and deliver real-time diagnosis.

Remote sensing techniques are employed to keep an eye out for disease outbreaks in vast citrus plantations. These approaches include satellite imaging and airborne surveys.These methods can spot changes in vegetation health and locate diseased areas by examining the spectral signatures of citrus trees.The construction of disease risk maps using remote sensing data and machine learning algorithms facilitates resource allocation and focused disease management.

Early detection and prevention: Automated disease detection tools make it possible to identify citrus diseases early-even before any outward signs show up.

Using imaging technology and machine learning algorithms, these systems can continually monitor the health of citrus plants and identify small changes in plant physiology or leaf reflectance that point to the presence of illnesses. Early disease diagnosis enables quick disease control techniques, such targeted pesticide administration, removal of affected plants, or modification of irrigation and fertilisation practises.

Decision support systems: Technologies for citrus disease detection can be included into decision support systems, which give farmers access to real-time data and advice on how to manage diseases.

These systems aggregate data from several sources, including weather, disease occurrence in the past, and disease detection data now available, to produce actionable insights and direct farmers in making decisions about disease management methods. Citrus growers and the agricultural sector as a whole stand to gain significantly from the use of citrus disease detection technologies in practical settings. Early intervention is made possible, crop losses are decreased, resource use is maximized, and it helps to develop sustainable and efficient disease management techniques.

2.2 Organisation of Project Report

The project report is organized as follows: In section (2) we discuss the problem statement and the proposed solution. We also take a look at the systems that exist today and the drawbacks they face.Section (3) takes a more in-depth look at various software based solutions that exist, with a survey on existing literature available. Section (4) looks at the architecture of the proposed solution with an overview of the system design, utilizing system block diagrams and data flow diagrams. Section (5) dives into the Implementation of the solution, by describing the hardware and software requirements, along with dataset descriptions and implementation details. Section (6) describes our dataset being used Section (7) looks at our experimentation process and the obtained results. Section (8) summarizes our findings and concludes the paper.

3 Problem Statement and Proposed Solution

3.1 Problem Statement

The goal of this project is to create a system that employs deep learning techniques to accurately identify citrus fruit and leaf diseases.The system should be able to identify good and unhealthy citrus fruits and leaves from photographs by analyzing them. Accurate disease diagnosis can assist farmers in acting quickly, putting effective treatments in place, and stopping the spread of infections. Manual identification of citrus fruit and leaf diseases is time-consuming and prone to errors.Traditional methods rely on visual inspection by experts, which can be subjective and inefficient.Therefore, there is a need for an automated system that can accurately detect and classify citrus diseases based on images.

3.2 Existing Systems

There are numerous approaches and technologies for detecting citrus diseases that have been created and put into use. Here are a few noteworthy instances:

Spectral imaging and hyperspectral imaging: These imaging techniques make use of sensors that can record images at a variety of wavelengths, including visible and infrared spectra. These photos offer fine-grained spectral data that can be examined to find patterns and symptoms of particular diseases in citrus plants. These technologies can precisely diagnose and categorise citrus diseases by examining the distinctive spectral signatures connected to various diseases.

Digital image processing and computer vision: Computer vision algorithms and digital image processing methods have been extensively employed to identify citrus diseases accuracy. These systems examine photographs of citrus trees or fruits that were taken by drones or cameras. To recognise disease signs such leaf discolouration, lesions, or fruit anomalies, various image processing techniques are used, such as segmentation, feature extraction, and pattern recognition. Convolutional neural networks (CNNs) and other machine learning methods are frequently used to increase the precision of disease identification.

Smartphone Apps: Several smartphone apps have been created to help citrus producers identify diseases. These apps take pictures of citrus trees or fruits using the smartphone's built-in camera. The app's built-in machine learning models and image analysis algorithms are then used to process the photographs. The app offers recommendations for disease management techniques, delivers real-time disease diagnostics, and might even give users access to expert consultations or disease knowledge libraries.

Geographic Information Systems (GIS) have been used in conjunction with remote sensing technology, such as satellite imaging and aerial surveys, to conduct extensive citrus disease surveillance. These systems evaluate the condition of citrus orchards' vegetation and physical health using satellite photos or aerial photography. Disease outbreaks and patterns of their spatial distribution can be found by examining changes in vegetation indices, such as the Normalised Difference Vegetation Index (NDVI), which enables resource allocation and targeted disease control.

Portable Diagnostic Devices: To facilitate quick on-site disease diagnosis in citrus plants, portable diagnostic devices have been created. To identify certain pathogens or disease markers, these devices employ a variety of methodologies such as immunological assays, nucleic acid-based diagnostics, or biosensors. According to the diseases found, the gadgets' quick and accurate results enable farmers to act right now.

These already-in-place systems for detecting citrus diseases provide farmers with useful tools and technology to help them monitor and manage illnesses in citrus crops. Future improvements in illness detection accuracy, efficacy, and accessibility are anticipated to be made possible by ongoing developments in imaging technologies, computer vision algorithms, and portable diagnostic tools.

3.3 Existing Solution

A Multilayer Convolutional Neural Network is proposed for the classification of citrus and leaves infected with different diseases.

ACQUISITION AND SPLITTING OF DATASET: At every stage of an image analysis investigation, from training to assessing algorithms, datasets are required. The citrus dataset and the Plant Village dataset both contributed 2293 photos to this investigation. The benchmark repository, known as Plant Village, intends to give researchers knowledge on the health of plants. Five groups of infected photos were created, each representing a distinct citrus fruit and leaf illness. The diseases we looked at in the datasets were Black spot, canker, scab, Greening, and Melanose. The dataset is divided into three sections: training data, test data, and validation data. The proposed CNN model was introduced utilising the Keras library, TensorFlow, Intel Core m3 7th Gen, 64-bit operating system, and 8GB RAM on an Intel Core m3 7th Gen, 64-bit operating system.

1) TRAINING DATA:80% of the training data is used to create a CNN model, albeit this amount may vary based on the needs of the experiment.The CNN model, which attempts to learn from the training data set, is trained using it. The training data consists of both the input and the expected result.

2)TEST DATA: The CNN model is tested using a test set that represents 20% of the original data. Once the model has received the necessary training, it is used for the evaluation procedure.

3) VALIDATION DATA: The reduction of overfitting and underfitting, which happens when the training phase's efficiency is significant and performance suffers when evaluated with new data, can also be accomplished through the use of data validation. As a result, a 10% validation set is meant to guard against efficiency problems while doing parameter tweaking. For this, we used automated dataset validation, which reduces overfitting and offers a fair model evaluation.

The following modules make up the suggested method: (i) input picture pre-processing; (ii) CNN layer-1; (iii) CNN layer-2; (iv) Flatten layer; and (v) classification.

Layer 1 of CNN: This is the first convolutional sheet of the CNN model. The input image matrix is subjected to a convolutional process to produce a feature map.

Layer 1 of Maxpooling: When the CNN layer- 1 characteristics are relayed to this layer, their size is condensed. This layer lessens the filters' sensitivity to noise and fluctuations.

Layer 2 of CNN: The second convolutional layer performs operations in a manner similar to the first, with the exception that the first layer gathers low-level picture features while the second layer extracts high-level characteristics.

Layer 2 of Maxpooling: The same purpose of reducing the dimensionality of the feature map is carried out as in Maxpooling layer 1 in this layer.This layer produced an array of feature pools.

Flatten Layer: The matrix, which was acquired from the second Maxpooling layer, is subjected to the flattening method. The pooled feature matrix is transformed into a feature vector, which is a column or vector, by this layer.

Classification Layer: Both the SoftMax activation functions and the feature vector obtained from the flatten layer are employed in this layer's classification. The photos of citrus fruit and leaves are then examined for disease classification.

The main justification for choosing the convolutional neural network as the suggested technique is its effectiveness in image identification and recognition tasks. With applications in robotics, self-driving automobiles, medical imaging, defence, and drones, it currently reinforces significant breakthroughs in the field of computer vision.

1) INPUT IMAGE The input image of the citrus fruit or leaf is composed of a row of pixels that fills the entire width and height of the display. The "input shape" parameter is used to create a three-dimensional input image matrix. The citrus fruit or leaf picture from the input is now prepared for a convolutional layer, which will further process the images.

2)CONVOLUTIONAL LAYER-1 Feature extraction is the function of the convolutional layer, the first layer of a CNN. In the convolutional layer, the input image matrix and learnable filters (small matrix) are convolved to produce the feature matrix. In order to construct a function map F, a filter matrix K is applied to the image matrix I for convolutional use. The purpose of ReLU is to portray non-linearity in the CNN model.

3)MAXPOOLING LAYER-1. The pooling layer, often referred to as the sub-sampling layer, creates a down-sampled version of the input function mappings after the convolution layer. We have performed a Maxpool operation on the feature map for our proposed model to reduce its size.

4) CONVOLUTION LAYER-2 The input (pooled functional matrix) obtained in the Maxpooling layer is used to extract high level properties in the second convolution layer. The computation for the second convolution layer is the same as for the first convolution layer.

5) MAXPOOLING LAYER-2 The scale of the matrix is to be decreased by the second max-pooling layer. The first layer of Max-pooling's second layer of pooling is computed identically.

6) FLATTEN LAYER The output (pooled function map) from the second max pooling layer is used by this layer. The flattening layer's objective is to transform a pooled feature matrix into a column or feature vector. By rebuilding the function, the features or components of the pooled feature map M are transformed into feature vectors within this layer.

7) CLASSIFICATION By adjusting a dense layer with numerous neurons using softmax functions, the probability for the various types of citrus fruit/leaf diseases are computed for classification.

8) APPLYING ACTIVATION FUNCTION At the classification layer, the softmax activation functions are used.

3.4 Proposed Solution

We have implemented the citrus fruits and leaves diseases detection model in four transfer learning models so that we can compare the accuracies and choose the model with highest accuracy and least execution time.

VGGNET 16 MODEL: The VGGNet 16 model is a deep convolutional neural network architecture that was invented by Simonyan and Zisserman from Visual Geometry Group (VGG) at the University of Oxford. It was created by Simonyan and Zisserman. It is frequently employed for a range of computer vision applications, such as picture segmentation, object recognition, and image classification. In order to categorise unseen items, VGG Net has mastered the art of extracting features (feature extractor). By increasing the depth of the CNNs, VGG was created to improve classification accuracy. For object recognition, VGG 16 and VGG 19, with 16 and 19 weight layers, respectively, have been employed. VGG Net runs a stack of convolutional layers with a fixed filter size of 33 and a stride of 1 on the input of 224X224 RGB pictures. Between the convolutional layers, there are five max pooling filters integrated to down-sample the input representation (image, hidden-layer output matrix, etc.). Three fully connected layers with 4096, 4096, and 1000 channels each follow the stack of convolutional layers. A soft-max layer is the final layer. There are 16 layers in the VGGNet 16 architecture, including 13 convolutional layers and 3 fully linked layers. The fundamental principle of the VGGNet architecture is to continually apply modest 3x3 filters to obtain spatial information while maintaining a shallow depth of the network. This makes it possible to learn more discriminative characteristics. Input Layer: A 224x224x3-pixel picture serves as the network's input. Convolutional Blocks: The network starts with two sets of convolutional layers, each with 64 filters (block1$_conv1andblock1_conv2).Next,amax -$
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VGGNET 19 MODEL: The VGGNet 19 model is an extension of the VGGNet 16 architecture. This VGGNet 19 model network receives an RGB image with a fixed size of (224 * 224), indicating that the matrix has the shape of (224,224,3). The mean RGB value of each pixel, calculated throughout the whole training set, was the only preprocessing that was carried out. Then, in order to cover the entirety of the image, kernels of (3 * 3) size with a stride size of 1 pixel were employed. To maintain the image's spatial resolution, spatial padding was applied. Max pooling was carried out with stride 2 over a 2 * 2 pixel window. Rectified linear unit (ReLu) was employed after that to add non-linearity to the model in order to enhance classification accuracy and computation time. As opposed to earlier models that used tanh or sigmoid functions, this one performed far better. Then, three completely linked layers were implemented, the first two of which were 4096 in size. The third layer, a softmax function, followed by a layer with 1000 channels for 1000-way ILSVRC classification. Input Layer: A 224x224x3-pixel picture serves as the network's input. Blocks of Convolution: The network begins with two sets of convolutional layers (block1$_c$onv1andblock1$_c$onv2), eachwith64filters, andthenalayerofmaximumpooling(block1$_p$ool).Twoconv
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c. Projection Layer: A further 1x1 convolution is used to get the number of channels back to the desired level in the projection layer. By expanding the channels and then effectively reducing the dimensionality again, the model may capture more fine-grained characteristics thanks to the usage of inverted residuals. The MobileNetV2 architecture is made up of a number of stacked inverted residual blocks. Depending on the size and accuracy of the model that is needed, the number and placement of these blocks can be changed. Linear bottlenecks are a feature of MobileNetV2 that replace non-linear activations like ReLU with linear activations. This reduces information loss, especially in shallow layers, that may occur in depthwise separable convolutions. Similar to MobileNet, MobileNetV2 adds the width multiplier and resolution multiplier hyperparameters to regulate the model's dimension, accuracy, and computational complexity. Fully Connected Layers: Similar to previous CNN architectures, MobileNetV2 often concludes with a few completely connected layers and a softmax layer for categorization. While retaining a comparable degree of efficiency, MobileNetV2 delivers greater accuracy than the original MobileNet. By introducing inverted residuals, linear bottlenecks, and better architectural design decisions, it addresses some of MobileNet's drawbacks. Many computer vision tasks use MobileNetV2, especially in contexts with limited resources like mobile devices and embedded systems.

We have also implemented the backend logic alongwith a simple user-friendly frontend graphical user interface (GUI) which is easy to use for farmers. The frontend takes an image from a folder on the desktop and when analyse image is clicked, the input image is sent into the convolutional neural network, the image is subjected to varying layers of convolutional layers, maxpooling layers and fully connected layers with activation functions. The disease with the highest probability is the disease detected in the input image. After the disease is detected, the disease name, type of the disease and the remedy to eradicate the disease and the respoective fertilizer is suggested to the users.

3.5 System Requirements

Hardware Specifications:

Processor	Dual Core.
Speed	1.1 G Hz.
RAM	8 GB (min).
Hard Disk	20 GB.

Programming Language:

Operating System	Windows 10.
Technology	Machine Learning.
Front End	GUI-tkinter.
IDLE	Python 3.7 or higher.

Front End/Back End Tools: Python 3.7 or higher

4 Literature Survey

1.W. Gomez-Flores (et.al) [1]: Huanglongbing (HLB) disease affects the citrus production which results in a huge economic loss to the farmers. Huanglongbing is detected using convolutional neural networks which is primarily based on computer-vision systems.

The CNN architectures have convolution kernels and pooling layers which extract feature vectors[1]. As depth of CNN increases, the dimensions of element maps lower to activate finer functions. A connected layer along with a softmax activation classifies the images. To train CNN based systems there is difficulty in collecting large datasets.The CNNs which are already pre-trained tuned to differentiate Huanglongbing, abnormalities and healthy cases of citrus. In Transfer learning large datasets is used for training the CNN model and fine tuning is used to transfer learned parameters to smaller datasets. Also, a hand-crafted feature based conventional method was evaluated.

VGGNet shows the highest accuracy while classifying the disease as it is the deepest series network. VGGNet has more network depth and higher trainable parameters. In series networks, an increase in network depth increases the training computational cost increases because of the increase in trainable parameters.

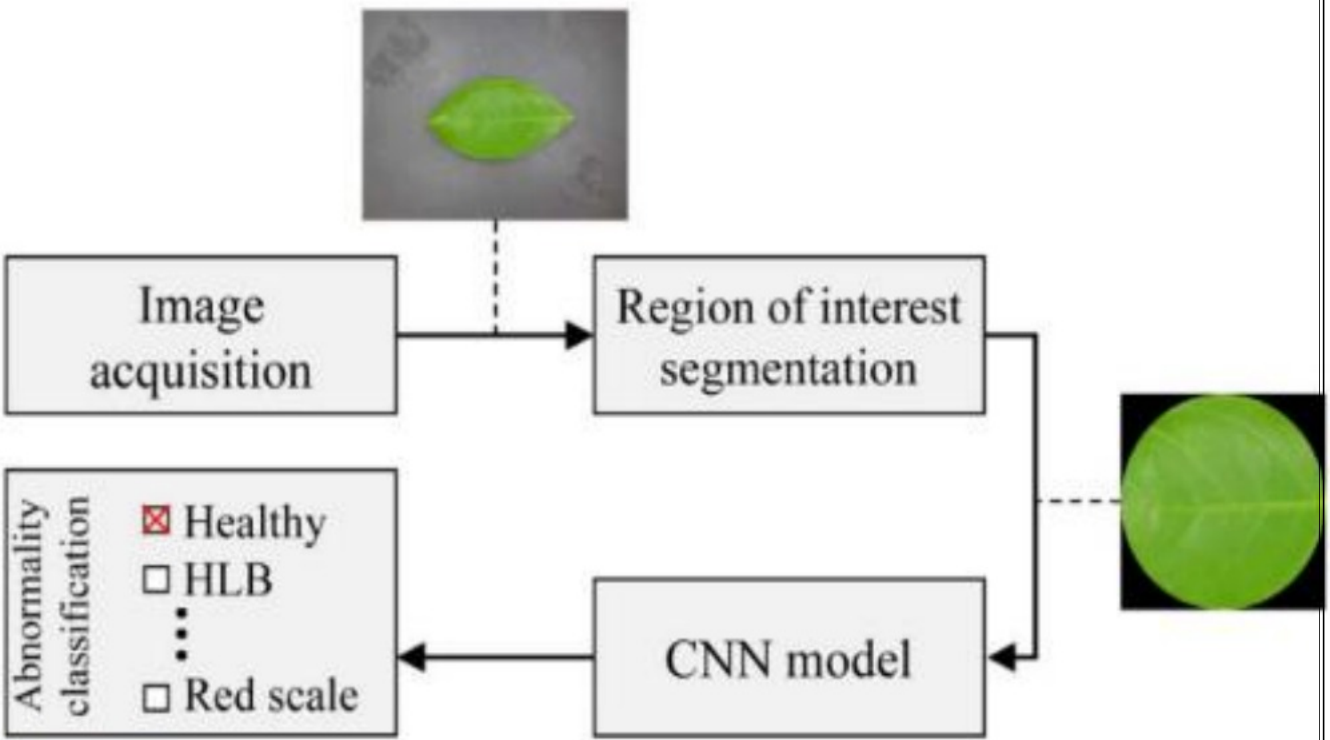

Fig 3.1:Detection system scheme for orange leaf classification[1]

2.M. Attique Khani (et.al) [2]: This study involves a single stream convolution neural network architecture with improved optimization is used for classification of citrus fruits and leaves diseases. Data augmentation is used for increasing the number of samples for training which is based on four operations- Improving brightness, pixel intensity adjustment, shadow removal and improving local contrast by flipping, rotating. Deep features are extracted as a feature vector from the newly trained model and with the help of the analysis of features extracted which contain some unnecessary information. Hence, Whale Optimization Algorithm is used which is improved.[2] Finally, classification is done through the best selected features using a neural network to compare performance with the other classifiers such as Gaussian Naive Bayes, SVM (linear and quadratic) and fine tree and then results are calculated.To store and collect information, MobileNet V2 has a new component known as the inverted residual. The main advantage of this is the proposed architecture had a better performance compared with the other methods in terms of time and accuracy.

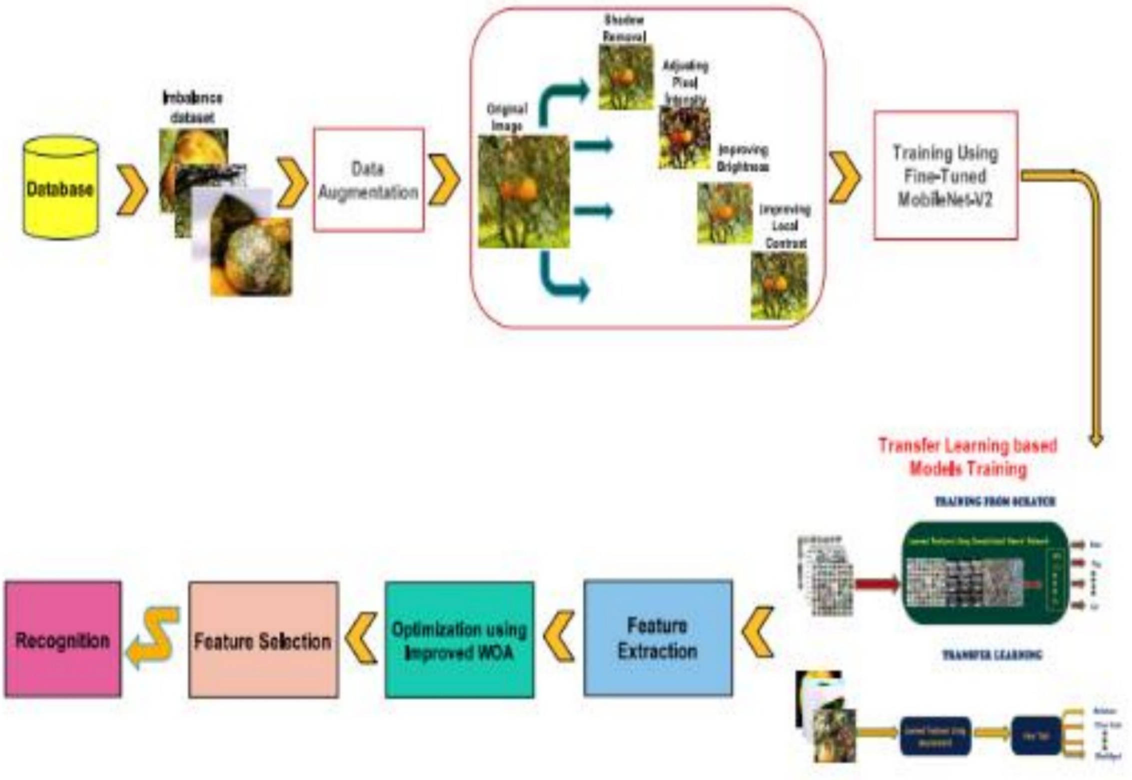

Fig 3.2:MobileNet V2 deep model[2]

3.W. Pan, J. Qin (et.al) [3]: Development in communication technology is driving newer advancements in broader areas. Mobile Service Computing has played a key role in always accessing services through mobile applications. The main aim is to DenseNet layers are mostly removed to reduce overfitting and prediction consumption. The DenseNet 201 is made up of 4 different types of dense blocks and a transition layer that connects every dense block. The bottleneck layers of 6, 12, 48 and 32 layers make up the dense block. The bottleneck layer is made up of BN-ReLU-Conv(1×1)-BN-ReLU-Conv(1x1), build a simplified densely connected convolutional neural networks (DenseNet) to provide a clear diagnosis system for disease classification[3]. Through the WeChat applet, this system is implemented on mobile devices where images are uploaded by users which displays results and suggestions. The simplification of the structure of DenseNet also reduces the consumption of prediction time. To fine-tune the simplified DenseNet, the data augmentation and dataset original dataset are used.

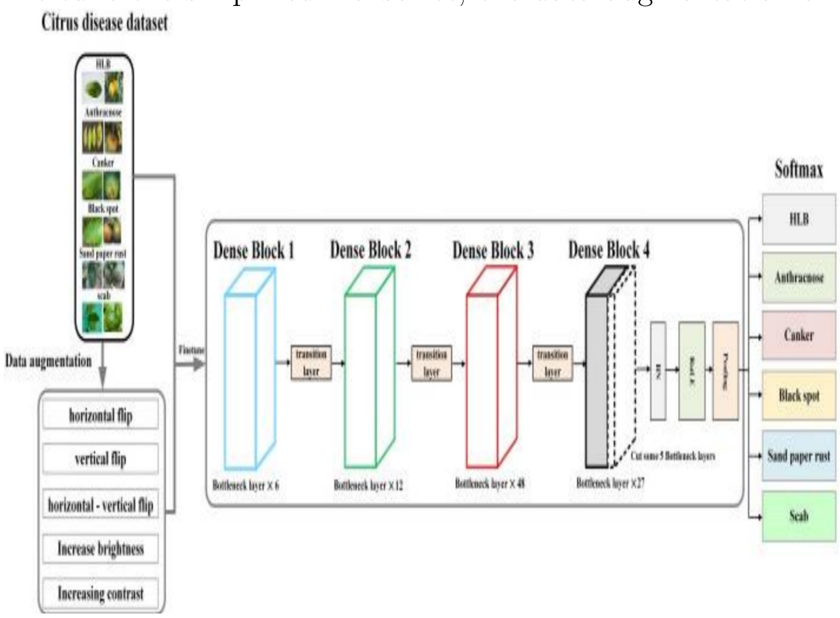

Fig 3.3:Simplified DenseNet training model [3]

4. C. Senthilkumar (et.al) [4]: They presented an automatic citrus disease detection involving Otsu-based segmentation process and Inception v2 feature extraction based ResNet. Random Forest algorithm is used as a classifier to classify and differentiate various kinds of citrus diseases. The first step is pre-processing where the image quality is improved. Pre-processing is done at two main stages: Contrast Enhancement where adaptive gamma correction (AGC) techniques are employed and Reduction of Noise, where Bilateral Filters (BF) is used to remove outliers in the image[4]. The second step is segmentation of images by Otsu model which is used in numerous image processing for threshold-based image segmentation and conversion of grey scale images to binary images.To obtain an efficient model, the class probabilities are determined iteratively.

The third step involves feature extraction by Inception ResNet V2 model, where the first layers are trained in extraction of low-level attributes comprising of edges, lines, and dots. A filter expansion layer is used after Inception block to increase the filter bank dimension before adding it to map the input depth. The extracted features of the images are classified into different classes by Random Forest classifier using Decision Trees from forests.

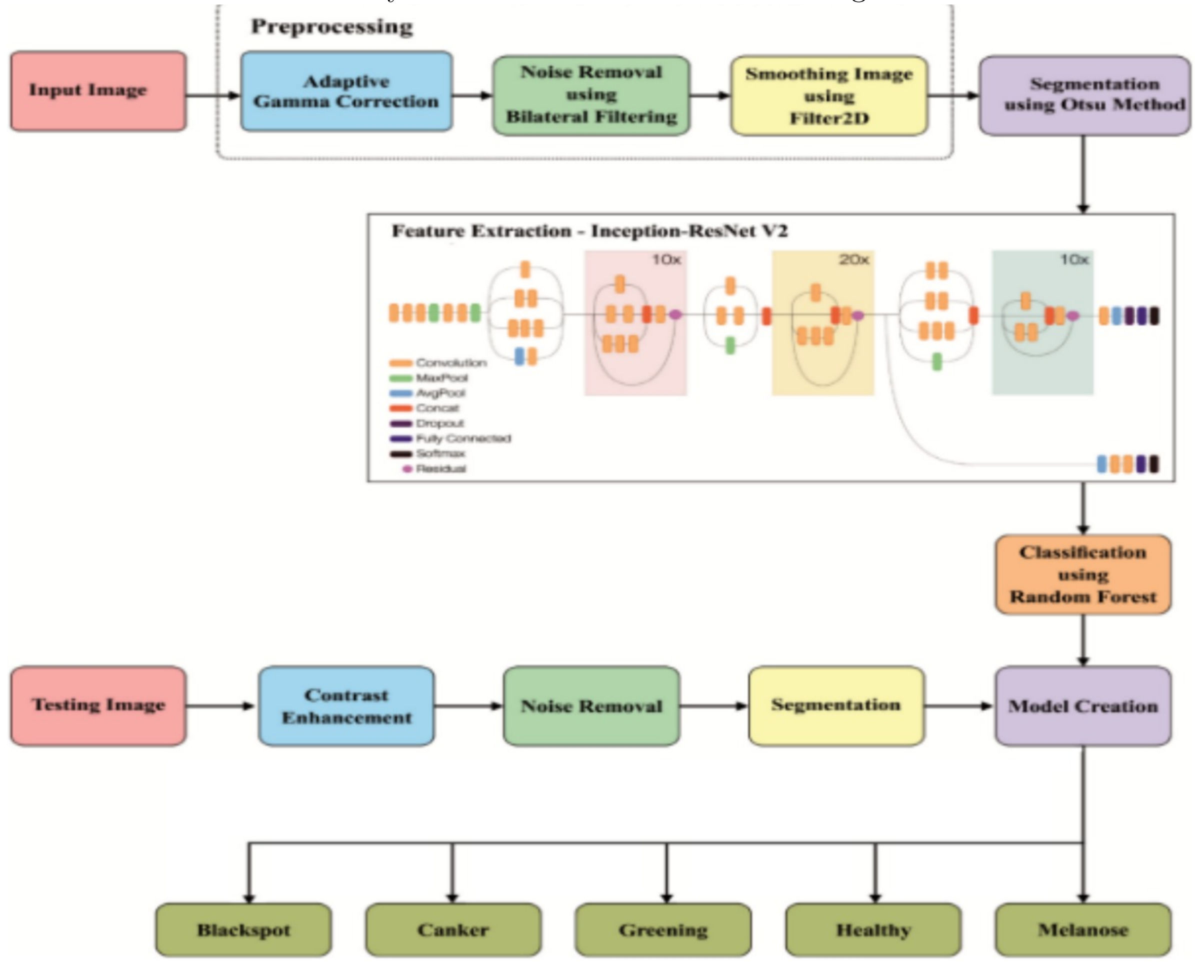

Fig 3.4:Otsu-based segmentation process with Inception ResNet V2 model[4]

5.S. Farhana Syed-Ab-Rahman (et.al) [5]: A two-stage deep Convolution Neural Network model is proposed using the leaf images and detecting the plant disease for classification of citrus diseases. This Faster R-CNN[5] based model consists of ResNet 101 feature extractor and finding the areas of the leaf with most disease affected regions using the Regional Proposed network. This helps reduce the training overhead by sharing the features between the RPN and the classifier. A loss function was used to compute the average loss obtained from the RPN model and classifier. The specified regions by the RPN network are not treated the same and the loss function of the RPN network represents the result of the model. Therefore, the result of the model is much contributed by the areas having larger probability of having disease patterns. The model gives the best performance for the reason of having RPN and the classifier which helps in the classification of target regions. This leads to decrease in false positives and these are caused by other portions of the image with less contribution to the target class.

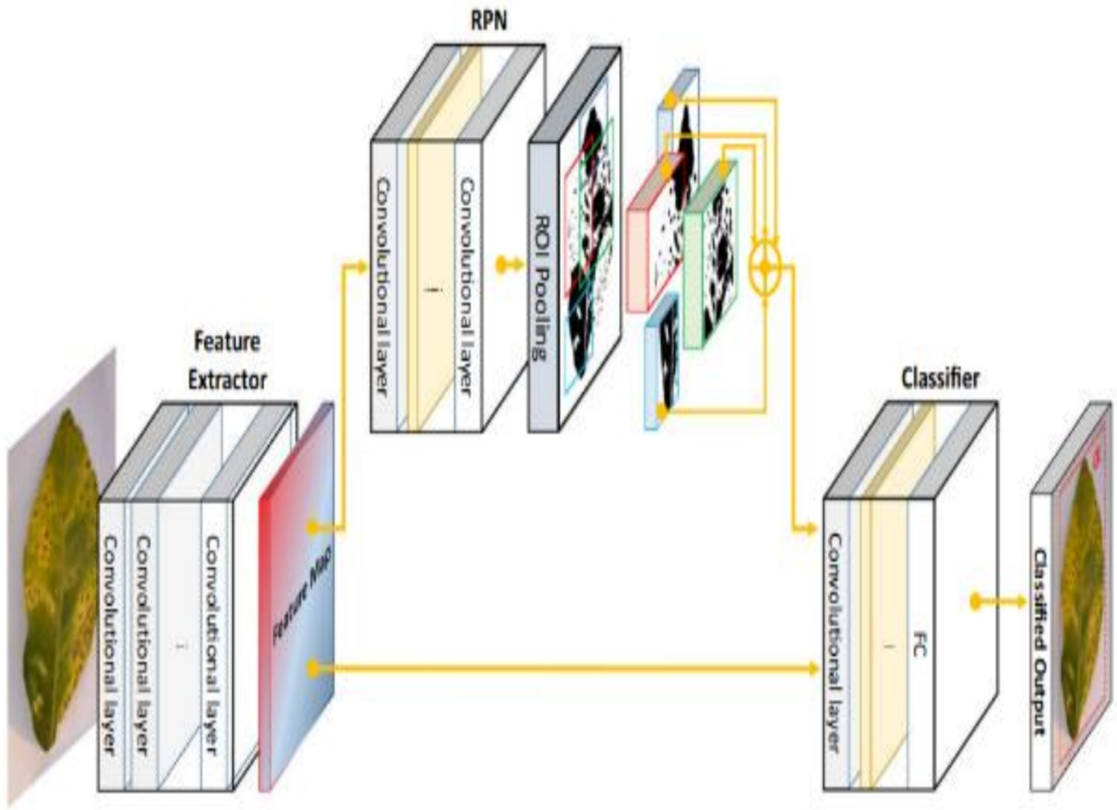

Fig 3.5:Faster R-CNN based convolutional neural network model[5]

6.A. Kumar Sainia (et.al) [**6**]: This study employed the outline of different image processing methods for detection of plant diseases. The stages of detection include extraction of features, pre-processing, classification and segmentation. Through this survey, the precision of segmentation has increased by the image processing strategies.Classification suitability can be controlled through the selection of five classification algorithms which are of prime importance. Finally, a model with hyperparameters is constructed with the algorithm having the maximum and excellent efficiency. The five techniques used in the analysis are K-NN, Naive Bayes, Artificial Neural Networks, Multi SVM and Random Forest [6]. K-Means clustering technique is being used as the most crucial strategy for segmentation of images. Different techniques are used to extract different features of the leaf like texture, color, shape, etc. but texture features provide good results. Texture of a picture is the one of the most important characteristics for the disease depiction, while K-NN and SVM use these characteristics.

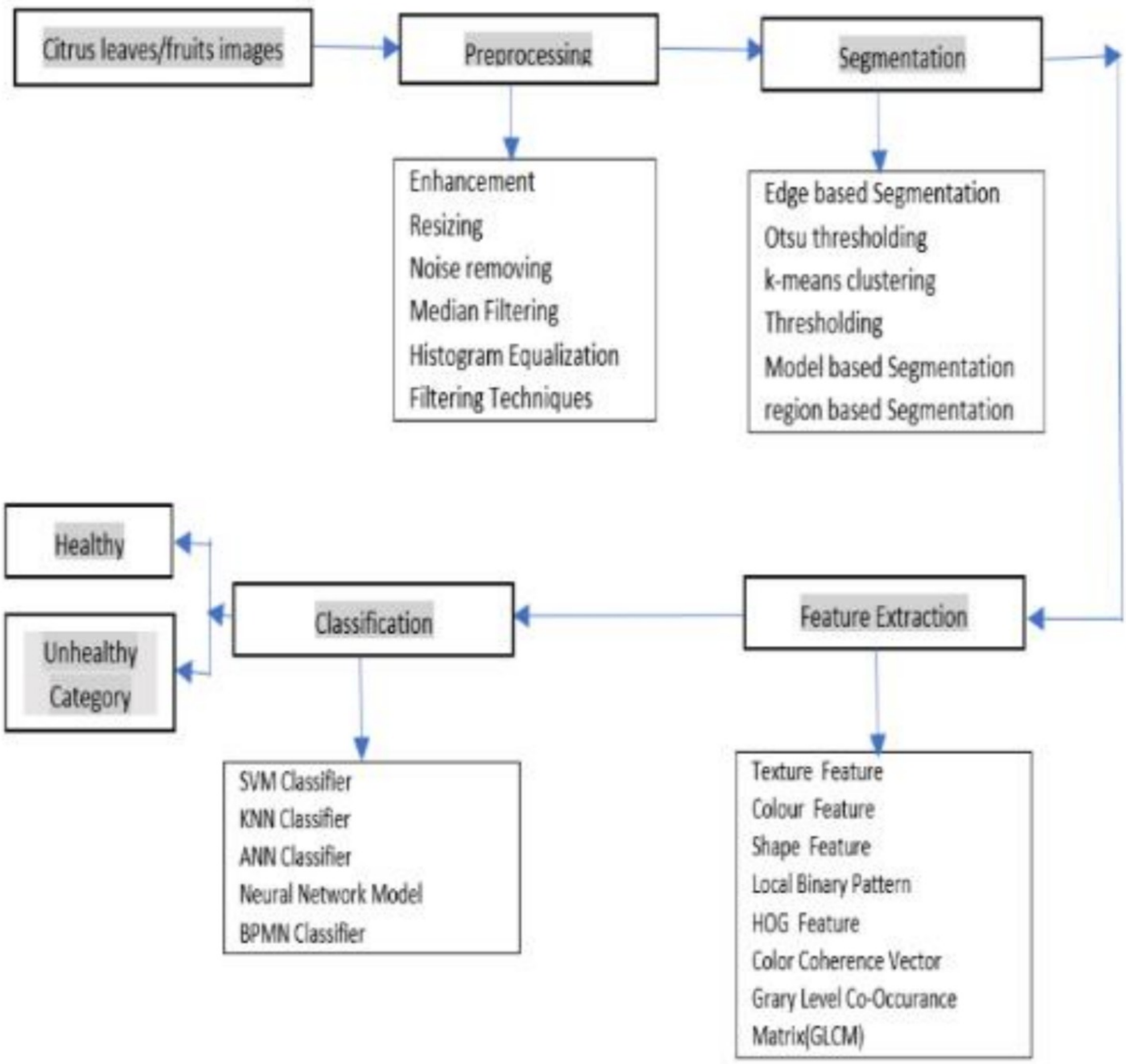

Fig 3.6:Structure of the model[6]

7. S. Janarthan (et.al) [7]: The deep metric learning model [7] was employed for disease classification in citrus plants.Preprocessing of citrus leaf and fruit images included background removal, patch creation, and augmentation. The framework involved dividing the individual leaf into five patches and classifying them as eligible or non-eligible. A trainable DCNN embedding module was used for computing embeddings and contrastive loss was utilized for training. Pretrained embedding modules facilitated clustering and computation of patch embeddings. The softmax layer, trained with categorical cross-entropy loss, resulted in a trained classification network for citrus diseases. During testing, leaf images were classified as normal or diseased using the learned classifier network. The Siamese network structure scored similarity between inputs, while the DCNN learned foreground features by removing the image background, enhancing model accuracy.

8.P. Dhiman (et.al) [8]: The version for detecting affected regions and severity stages of citrus fruit disorders consists of 5 modules [8]. The first module gathers images of citrus fruit, while the second module applies professional knowledge to label healthy and unhealthy images. Object detection and segmentation based on a graph are utilized in the third module to generate class-independent proposal regions. Similarity calculation is performed by grouping similar regions. In the fourth module, a fixed-length feature map is extracted using a transfer learning-based CNN network. The severity of the disease is determined in the last module using a multi-class sequential CNN with softmax function. The algorithm involves annotation of the input photograph, pre-processing of image features, computing texture gradients using LBP, and extracting HSV color histograms. The similarity is computed based on color, texture, and length. Testing on arbitrary photographs yielded accuracy rates of 96 percent for healthy, 99 percent for low degree, 98 percent for excessive degree, and 97 percent for moderate stages of the disorder.

9.M. Zhang (et.al) [9]: This survey proposes an improved method for citrus canker disease detection, addressing the issue of limited training images. Two techniques, feature augmentation and objective breakdown optimization, are employed to expand the dataset. A deep convolutional generative adversarial network is used to generate artificial samples, while feature magnification enhances required features to prevent overfitting to noise. The lightweight AlexNet with enhanced features and Siamese-based training parameter updating techniques accelerate training and minimize overfitting. The model is divided into two divisions, focusing on reducing the Siamese loss and updating parameters to achieve separable latent representations. The proposed approach improves the performance of the model by effectively addressing the scarcity of positive training samples and optimizing the training process. Customized architectures, such as DCGAN and mute layers, are utilized to augment the samples and enhance the learning process. Horizontal and vertical flipping, as well as sample rotation, are applied to augment the image samples in the dataset. The proposed method demonstrates promising results for citrus canker disease detection.

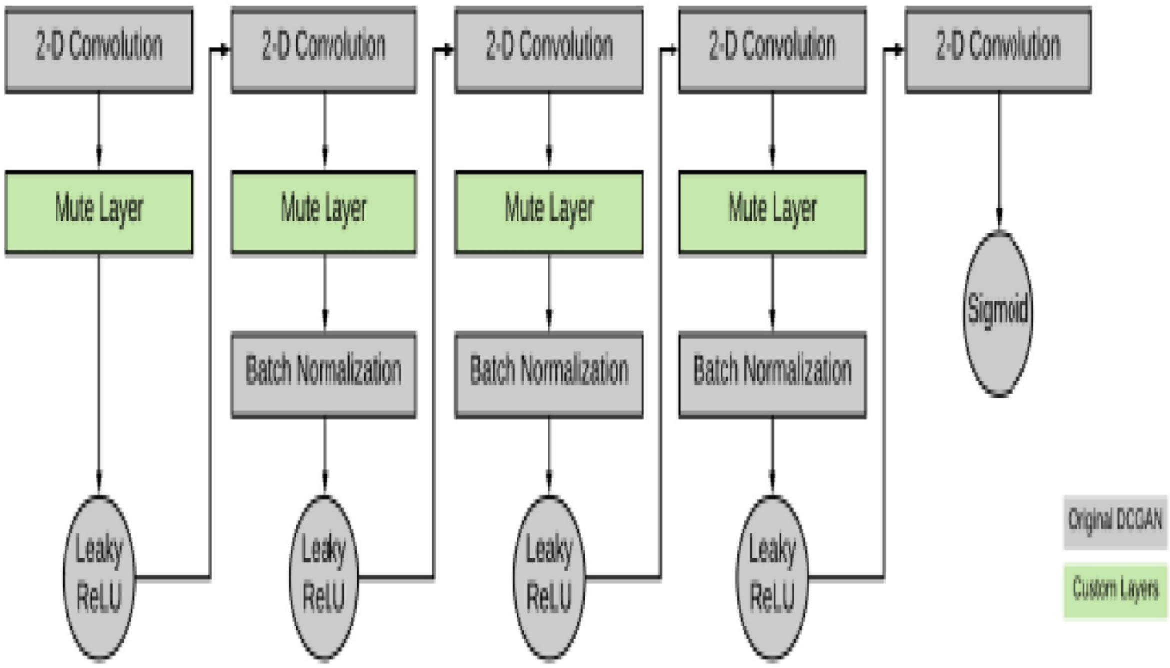

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Fig 3.91:The customized DCGAN with mute layers[9]

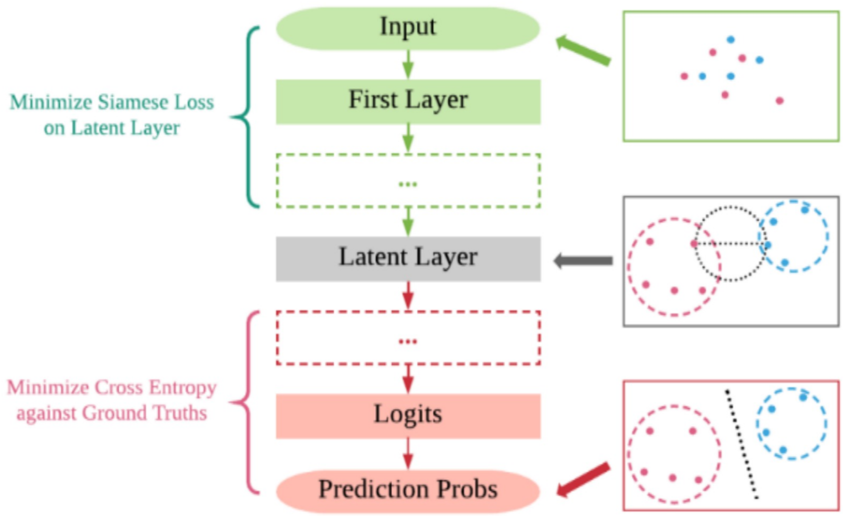


Fig 3.92:Steps involved in the DCGAN model[9]

10. Weiwei Cai (et.al) [10]: The growth process of citrus fruit plants is affected by environmental factors which results in diseases and poses as a huge threat to the crop yield. The method employed for the identification and classification of citrus diseases is based on MSRCR algorithm [10]involving enhancement of image and Laplacian optimized homomorphic filtering algorithm (HFLF-MS) pointing out the characteristics of the disease.DenseNet-121 is used as the backbone structure of DS MENet neural network where the regular convolutional layer in Dense block is substituted by depth separable convolutional layer thereby lowering the network parameters. The ReLU function is the cause of neuronal death and the ReMish activation function is used as a remedy to solve the problem and further in the improvement of the model robustness. A multi-channel fusion backbone enhancement (MCF) method for Dense Block processing further enhanced the focus on information related to citrus disease and trait extraction.10-fold cross validation was employed. All in all, one functional block, one classification block, three transitional blocks and dense blocks comprising of four together make up the DS MENet network structure. The workflow involves: Feature Block, which is DS MENet's first block, contains 7x7 convolutional layers and maxpooling layers of 3x3 size. The generalization ability of the model is increased and the convergence speed of the network is accelerated by the BN layer, the network robustness is improved by the ReMish activation function, both of which are in between pooling layer and convolutional layer. DenseBlock consists of 6 layers, five 1x1 convolutional layers, depth separable convolution of 3x3 size and 1 MSF backbone enhancement based convolutional layer. Before transferring a feature, the properties of all previous layers are used as input and the DenseBlock is directly connected to all these layers. Subsequent layers receive the output feature map. This arrangement lowers the mesh parameters, increases the feature utilization, transfer learning and tackles the problems caused by mesh deepening such as gradient vanishing or gradient explosion. The feature map is enhanced by the application of MCF method to the last convolutional layers. The reduction of network parameters along with the compression of the number of DenseBlock output channels is handled by the Transition Block containing convolutional layer of 1x1 size, Batch Normalization layer, ReMish and average pooling layers of 2x2 combination. The final part of the architecture is the classification block involving the Batch Normalization, ReMish, average pooling layers of 7x7 size andlinear layers. The results finally determined involves the usage of Softmax activation function in classifying the citrus disease

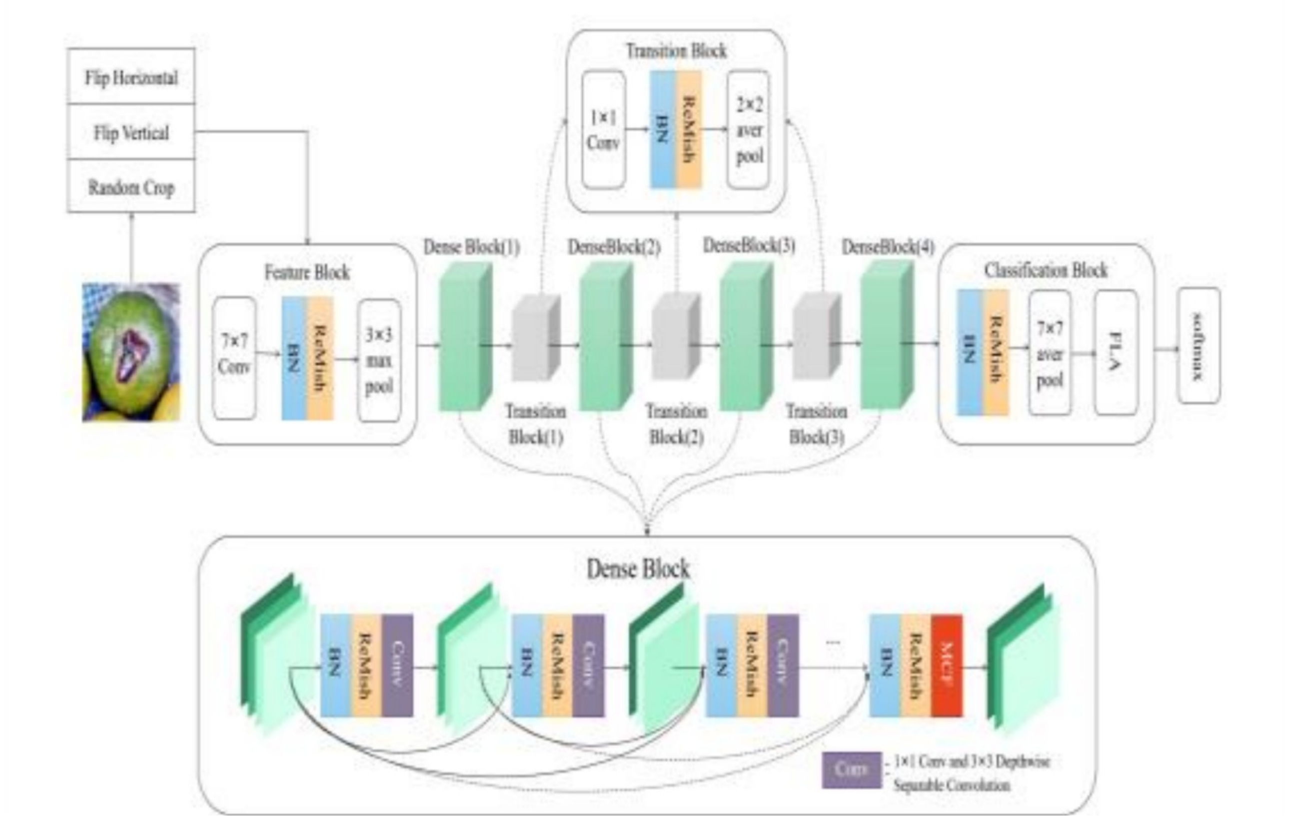


Fig 3.10:DS-MENet network architecture[10]

The detection of diseases on citrus fruits and citrus leaves is a challenging task as it requires years of expertise for humans to recognize and identify the symptoms of the disease. Instead, many machine learning techniques and deep learning techniques have made detection of diseases in fruits and leaves much easier. The main distinguishing feature comes at the accuracy with which the disease is predicted, and the time taken to execute to predict the disease. The computational resources needed to support the code should also be taken into consideration. When we went through research papers during the literature survey phase, we came across many techniques which solved the problem, but they varied in the accuracy rates and the time taken for execution. For the detection of Huanglongbling (HLB) disease [1], small sized datasets were used for training the neural network. Thus, transfer learning models are used to reduce training time and increase the model efficiency. VGGNet shows higher accuracy in classifying the disease as it is the deepest series network. VGGNet has more network depth and higher trainable parameters. In series networks, an increase in network depth increases the training computational cost increases because of the increase in trainable parameters. In another technique [2], the method is based on MobileNetV2 based on Improved Whale Control Entropy Optimization. It involves a single stream convolution neural network architecture with improved optimization is used for classification of citrus fruits and leaves diseases. Data augmentation is used for increasing the number of samples for training which is based on four operations- Improving brightness, pixel intensity adjustment, shadow removal and improving local contrast by flipping, rotating. The MobileNetV2 model is compared with other classifiers like Gaussian Naïve Bayes, SVM. MobileNetV2 has the highest accuracy as it has a component called depth wise separable convolution and inverted residual component. DenseNet -201 is another neural network which solves the problem of classification, which is made up of dense blocks. A Faster R-CNN method based on ResNet 101 also is efficient as it is based on Region Proposed Network (RPN). This reduces the training overhead by sharing the features between RPN and classifier. Thus, on comparing all these methods, we decided to implement the model using transfer learning models like VGGNet 16, VGGNet 19, MobileNet and MobileNetV2 model. These are the transfer learning models which have large architectures, and processes images at a faster rate. They are highly efficient in processing and give higher accuracy than basic models. They take less computational resources and lesser time to execute, increasing the overall performance of the model.

5 Architecture and System Design

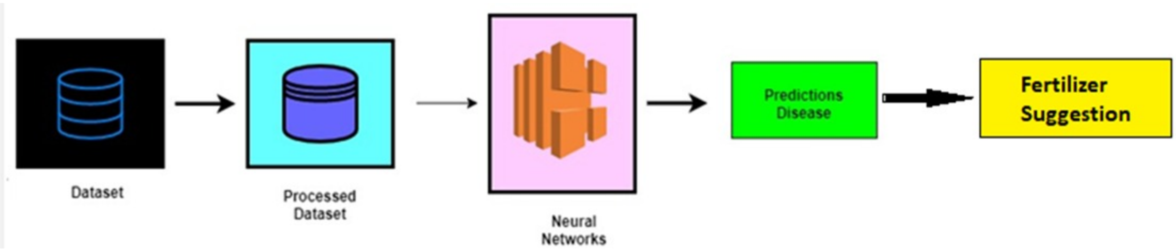


Fig 3 :System Block Diagram[3]

To perform image classification using a Convolutional Neural Network (CNN), the process typically involves several stages. Firstly, the data acquisition and preprocessing stage is crucial. This involves obtaining a dataset of images and preprocessing them to ensure they are in a suitable format for the subsequent steps.Once the input images are ready, they are passed through the first CNN layer, which applies a set of learnable filters to extract relevant features from the images. The output from this layer is then passed through a Max pooling layer, which reduces the spatial dimensions of the features while retaining the most important information. Next, the features are further processed by a second CNN layer, which applies additional filters to capture more complex patterns in the images. This is followed by another Max pooling layer to downsample the features and extract the most salient information.After the second pooling layer, the features are flattened, meaning they are reshaped into a vector form. This prepares the features to be fed into a classification layer.Finally, the flattened features are passed through a classification layer, which uses techniques such as fully connected layers or softmax regression to assign a probability distribution over the possible classes. The class with the highest probability is then selected as the predicted class for the input image.

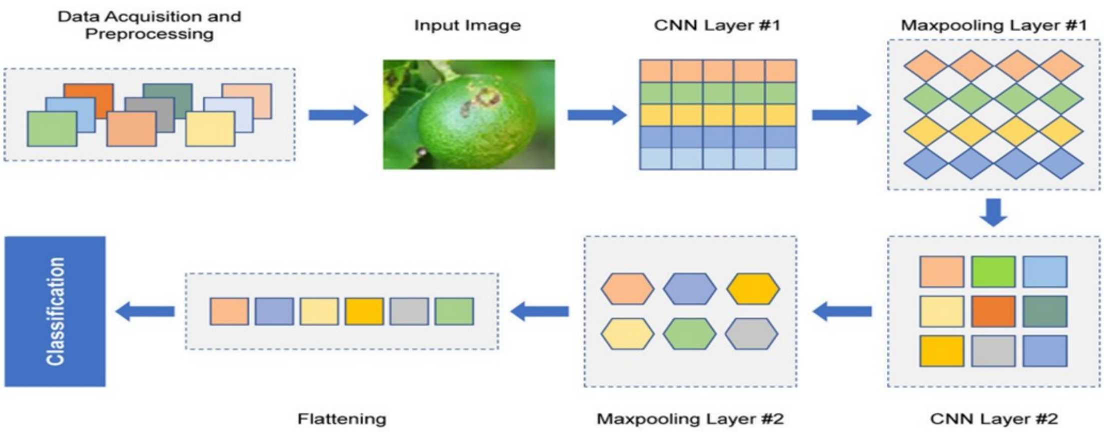
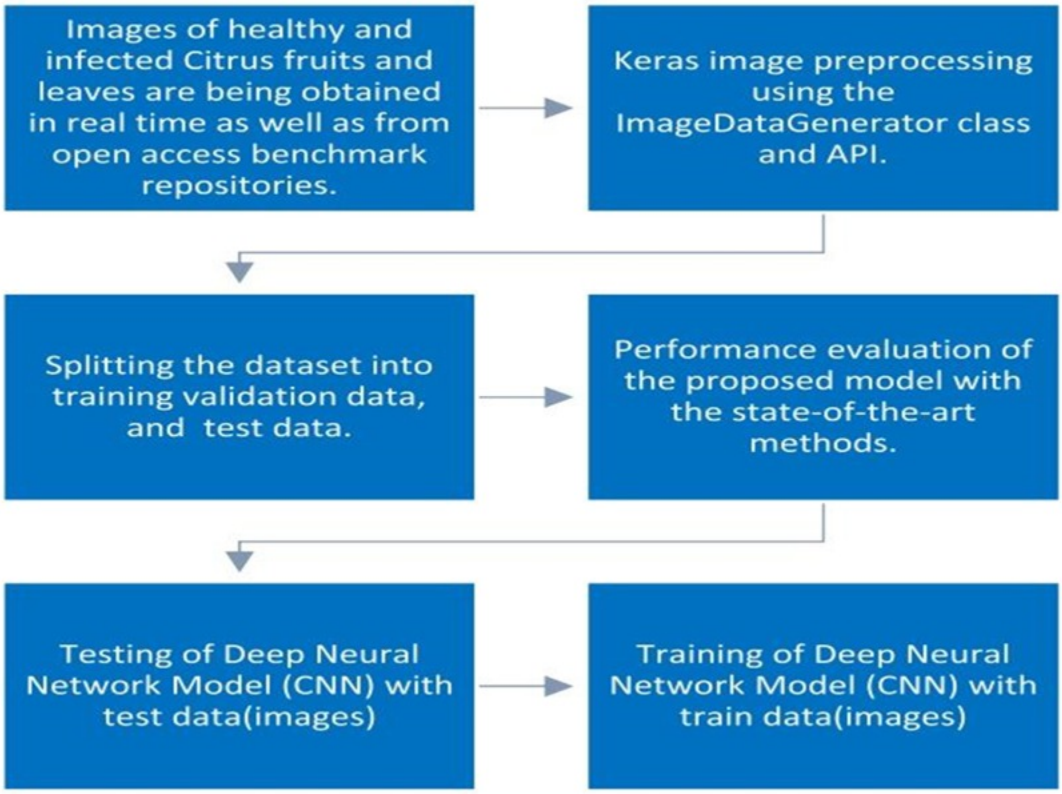
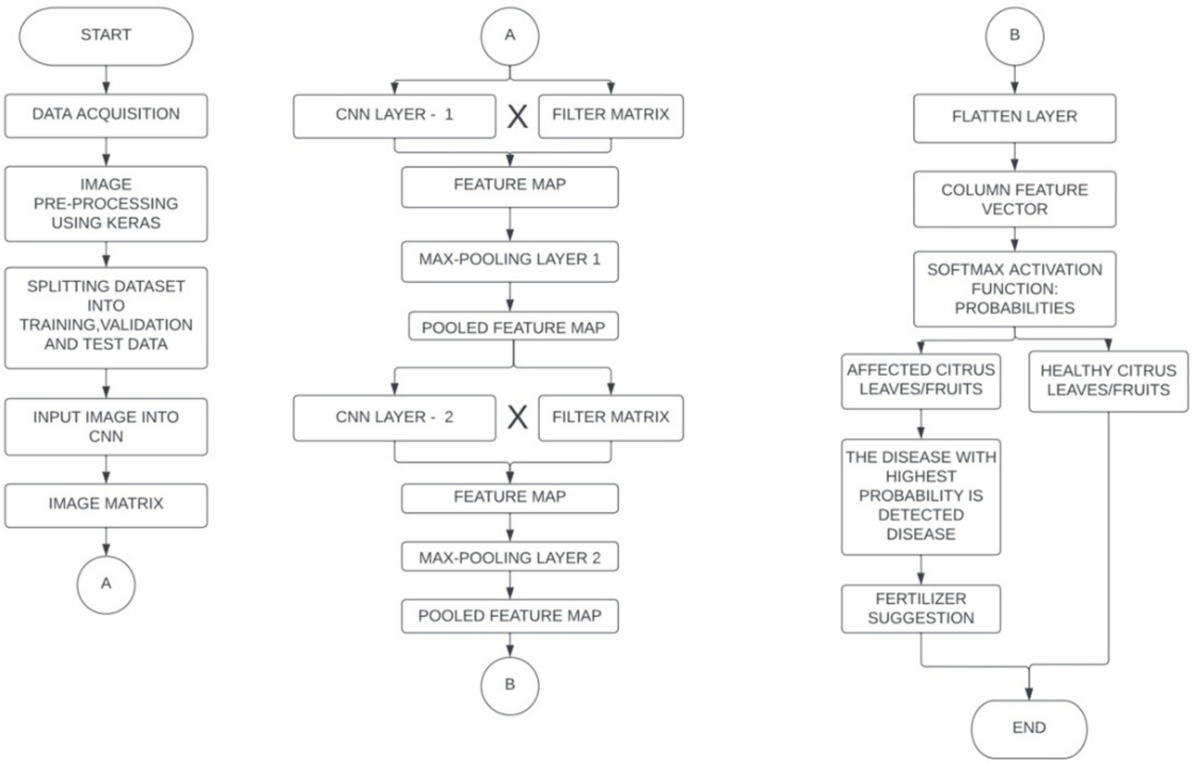


Fig 4 :Brief description of proposed system[4]

5.1 Data Flow Diagram



It normally takes several steps to conduct picture categorization using a Convolutional Neural Network (CNN). The stage of data collecting and preparation is critical first and foremost. In order to ensure that the images are in the right format for the following phases, this entails getting a dataset of images and preprocessing them.The first CNN layer processes the prepared input photos after which a set of learnable filters is applied to extract pertinent information from the images. After that, a Max pooling layer is applied to the layer's output, which lowers the spatial dimensions of the features while keeping the most crucial data. A second CNN layer then does extra processing on the features in order to identify more intricate patterns in the images. Another Max pooling layer is added after that in order to downsample the features and retrieve the most important data.The features are moulded into a vector form, or flattened, following the second pooling layer. This gets the features ready for a categorization layer to take them in.The flattened characteristics are then passed via a classification layer, which assigns a probability distribution over the potential classes using methods like fully connected layers or softmax regression. The projected class for the input image is then chosen to be the one with the highest probability.



The primary goal of the suggested solution is the classification of diseases such as black spot, canker, scab, greening, melanose, and healthy utilising the source picture and the proposed CNN model.

1) ANALYSIS OF THE IMAGE INPUTS :The image must initially be divided into pixels as the first stage. In the case of a coloured image, the image is represented as a three-dimensional matrix (7 x 8 x 3 in our example) with layers of red, green, and blue.

2) EXTRACTION OF DEEP CONVOLUTIONAL LAYER-1 FEATURE :After the input image has been analysed, the convolutional layer extracts features from the input image matrix. Within this layer, the layer matrix and the input image matrix are subjected to a convolutional process. Convoluting a filter matrix over an input image yields a resultant feature matrix.

3) REDUCING DIMENSIONALITY BY POOLING LAYER-1: The convolved feature map is put through a maxpooling method after the convolution layer obtained from the preceding layer of the CNN model is applied. The image matrix's size is decreased by the pooling layer.

4) LAYER-2 CONVOLUTIONAL FOR FEATURE EXTRACTION :The second convolutional layer's main goal is to use all of the filtering operations to extract high-level features from the feature map. A deeper layer can collect high-level features since the CNN model extracts features layer by layer.

5) MAX POOLING LAYER-2 FOR MINIMISING DIMENSIONALITY :Reducing the dimension

size to make it easier to detect features is the second pooling layer's goal.

6) FLATTENING A LAYER USING A FLATTER :The output from the second pooling is transformed into a long feature vector in this layer (pooled feature map).

7) CLASSIFICATION USING ACTIVATION FUNCTIONS:This module is where the picture classification happens. Classification of citrus fruit/leaf diseases is performed using the feature map input from the flatten layer. The probability of each of the five unique citrus fruit/leaf diseases is determined for this purpose using a softmax activation function. The probabilities for each of the five citrus illnesses are determined using the softmax function. The disease that is projected to be discovered in the image with the highest probability is shown.

5.2 Sequential Diagram

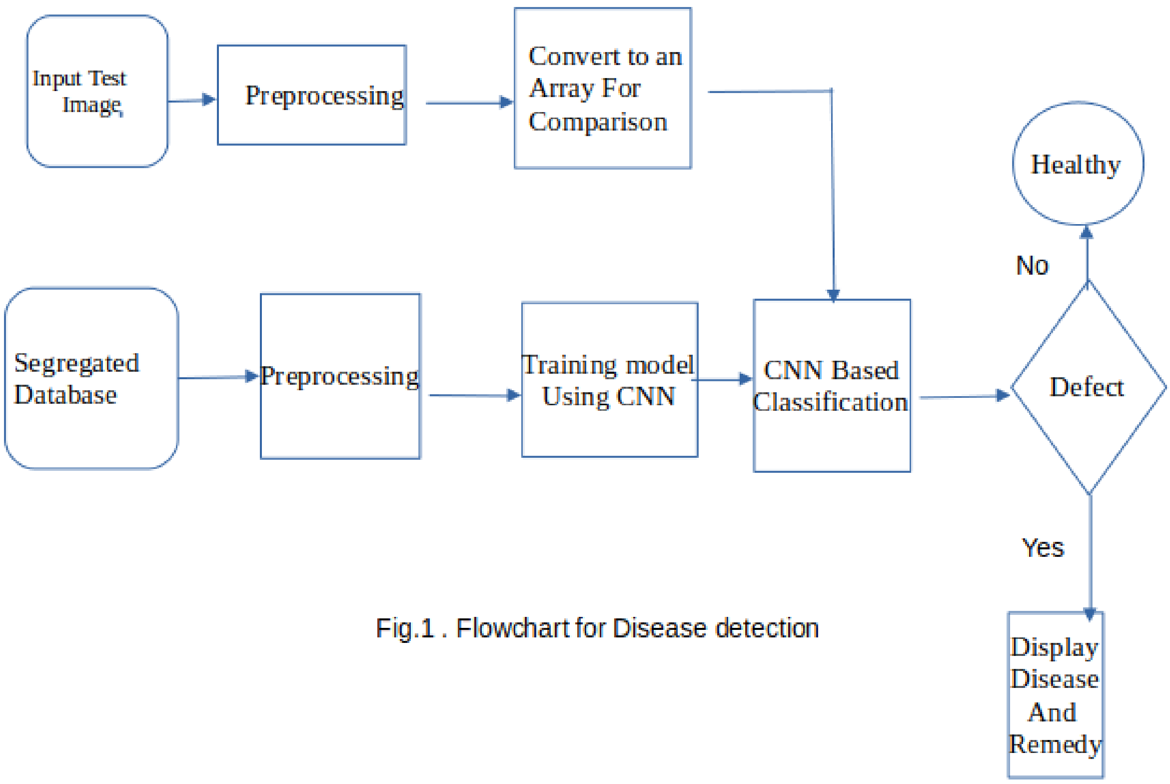
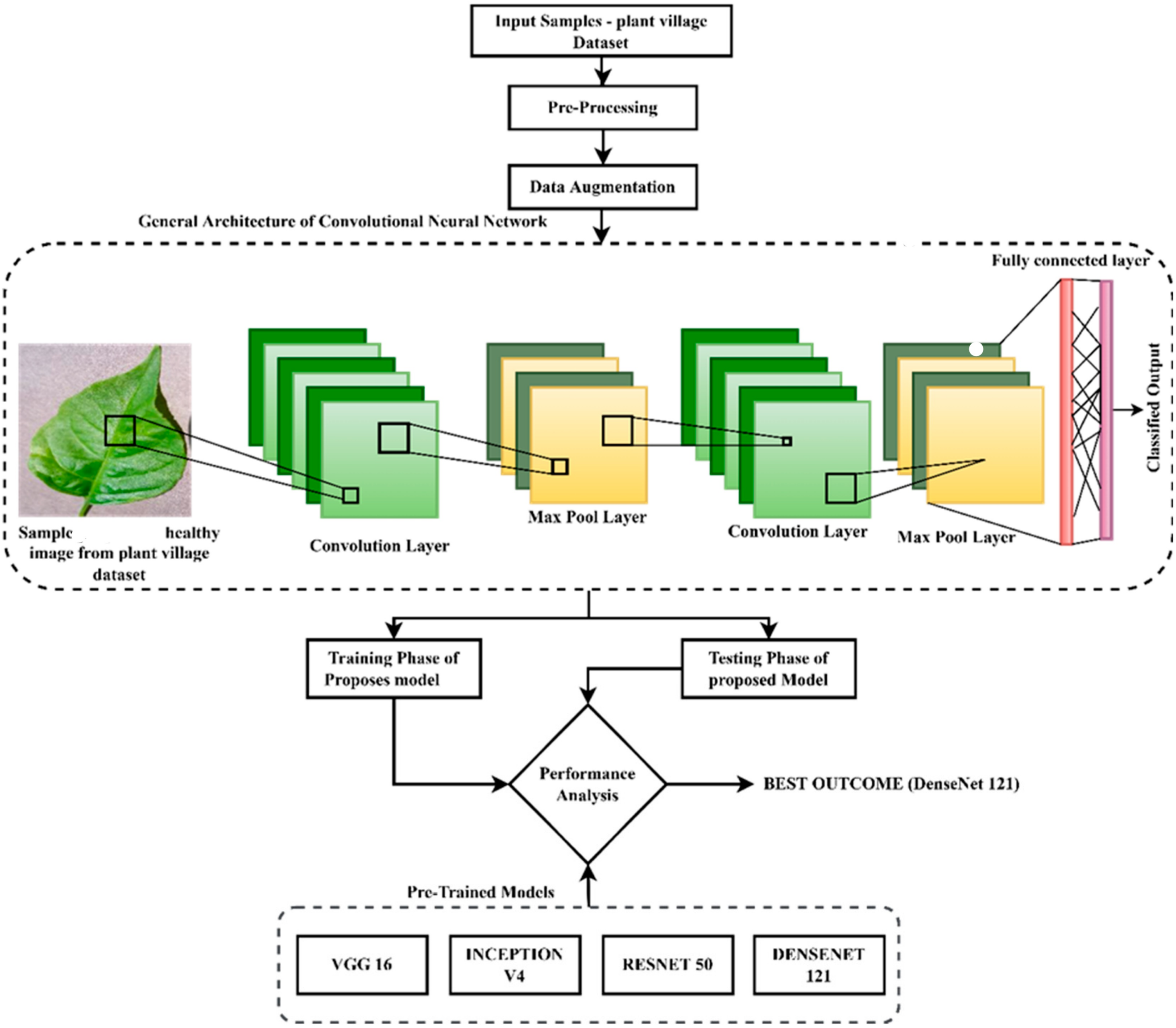


Fig.1 . Flowchart for Disease detection

5.3 Usecase Diagram



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6 Implementation

6.1 Implementation Platform

6.1.1 Hardware

Processor - Dual Core

Speed - 1.1 G Hz

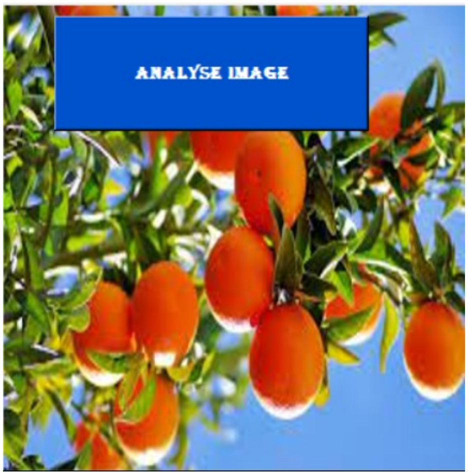
RAM - 8 GB (min)

Hard Disk-20GB

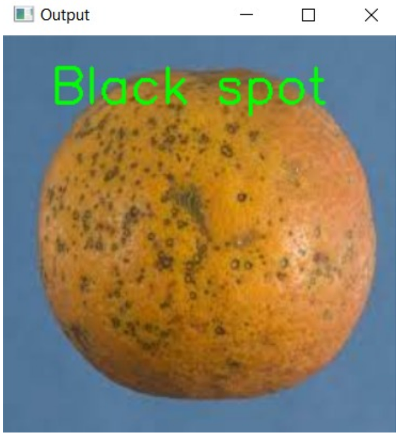
6.1.2 Software

6.2 Implementation Details

There are various processes involved in implementing autonomous detection of citrus fruit and leaf diseases using a deep neural network model. An overview of the implementation procedure is provided below: Data gathering: Gather a sizable set of pictures showing both healthy citrus fruits and leaves and pictures showing various pathologies. A variety of illness types, phases, and lighting conditions ought to be represented in the dataset. Data preprocessing: To ensure consistency and advance the learning process, preprocess the obtained photos. The photos are typically resized to a fixed size, the pixel values are normalised, and the dataset is augmented by applying random modifications including rotations, flips, and brightness tweaks. Dataset splitting: Split the dataset into three subsets: training set, validation set, and test set.

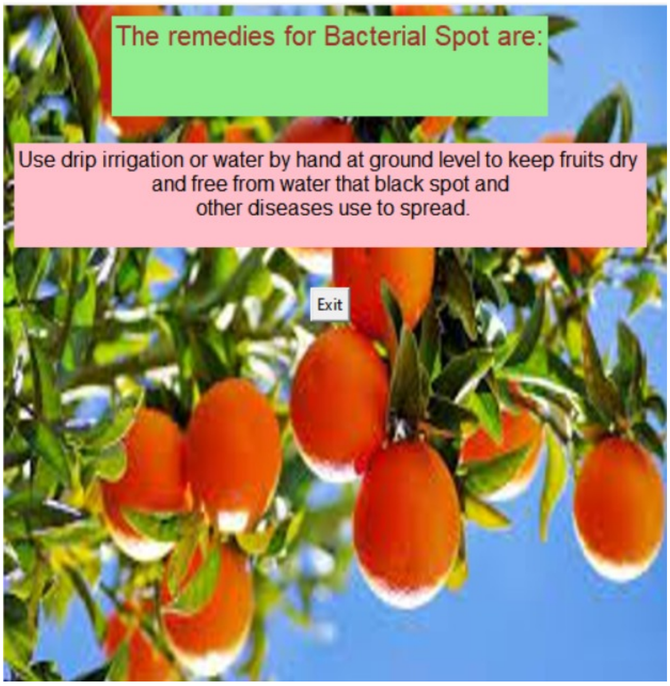


The training set is used to assess the performance of the final model, the validation set is used for hyperparameter tuning and model selection, and the training set is used to train the neural network.



Picking a model architecture: Select a deep learning architecture that is appropriate for the detection task. In order to classify images, convolutional neural networks (CNNs) are frequently employed. We used both our own architecture and transfer learning models like VGGNet and MobileNet

Model training: Apply the preprocessed dataset to train the chosen neural network architecture. The model gains the ability to separate pertinent features from the input photos during training and base predictions on those features.



The model gains the ability to separate pertinent features from the input photos during training and base predictions on those features. Using optimisation techniques like stochastic gradient descent (SGD) or Adam, the training procedure entails forward propagation, calculating the loss function, and backward propagation to update the model's parameters. Hyperparameter tuning: A neural network's learning rate, batch size, and regularisation methods can all be improved. The validation set is often used in this step to identify the optimal set of hyperparameters that maximise the model's performance.Model evaluation: Assess the performance and generalizability of the trained model using the test data. The performance of the model may be assessed using metrics like accuracy, precision, recall, and F1 score.Deploy the model in a production setting once it has demonstrated satisfactory performance. This may entail integrating the model into a programme or system that can take photos as input and output findings for disease detection.It's crucial to remember that the dataset's quality and diversity, as well as the appropriate choice and fine-tuning of the neural network architecture and hyperparameters, are critical to the implementation's success. As new diseases and variations occur, regular monitoring and updates may be required to guarantee the model's usefulness.

7 Dataset

There are 6 classes being considered for classification: 5 diseased classes and 1 healthy class. The five diseased classes are Black Spot, Citrus Canker, Greening, Melanose and Scab. Images of citrus fruits and leaves will be sent into the convoluitional neural network which extracts features from the images and classifies them into respective classes, that is, identifies the disease of the fruit or leaf present in the leaf

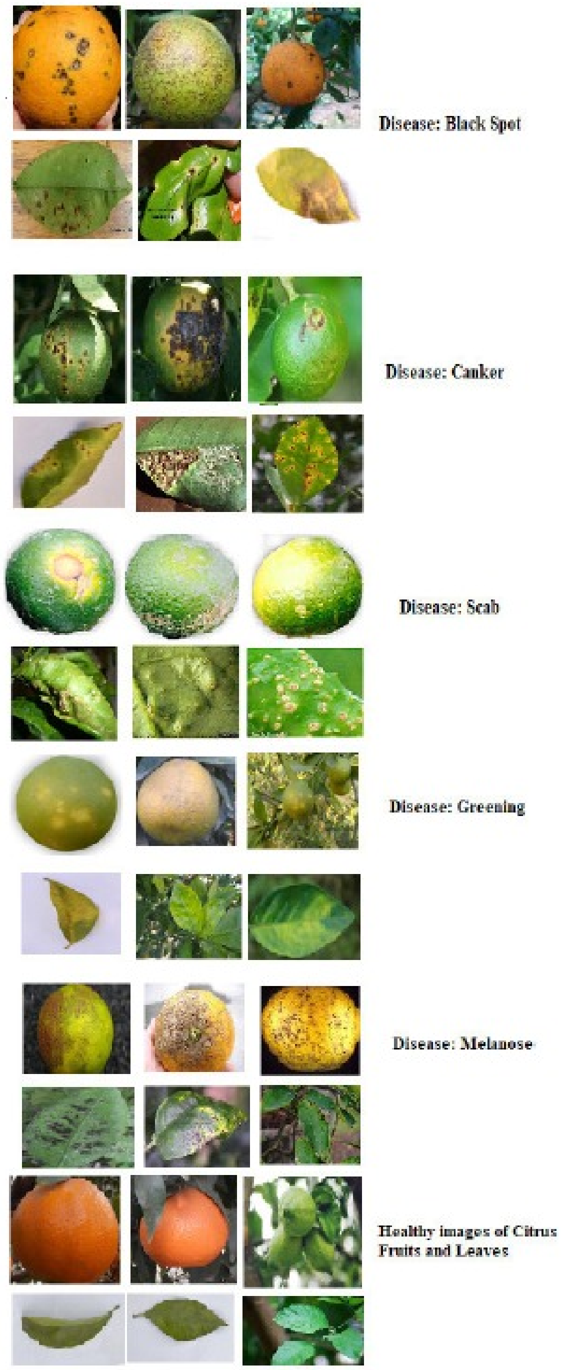


FIGURE 2. Sample dataset of citrus fruit and leaf images.

CITRUS BLACK SPOT


Phyllosticta citricarpa, formerly known as Guignardia citricarpa, is the fungus that causes citrus black spot. Citrus plants in subtropical areas are impacted by this Ascomycete fungus, which lowers fruit yield and quality. Fruit and leaf lesions are symptoms, with the latter being essential for inter-tree dissemination. Since there are currently few resistant citrus types, strict management and regulation are required to control this disease. A plant disease named Phyllosticta citricarpa has been linked to black spot on citrus plants' leaves. These strains are therefore covered by phytosanitary laws in both the European Union. Some endophytic bacterial species are inhibited from growing by the metabolites released by P. citricarpa, while others are stimulated.Under specific growing circumstances, a P. citricarpa isolate was shown to produce taxol, a substance with significant medical importance. Citrus plants are primarily infected by Phyllosticta citricarpa. But this fungus is also known to affect other plants, including guava, mango, and golden apple.Certain plants are more prone to the disease than others are. The most prone hosts are lemon and late-maturing citrus, such Valencia orange.Hamlin sweet oranges, tangerine- and mandarin-type citrus, and grapefruit are fairly susceptible hosts. Even though some hosts are more prone to Citrus Black Spot than others, any citrus plant that is nutritionally stressed has a higher risk of contracting the disease. The most frequent lesions are hard areas. Small, rounded, and sunken describe them. Hard spot lesions have an average diameter of 3 to 10 mm.They frequently have pycnidia in the centres of their gray-colored leaves, which have dark crimson to chocolate brown edges.There can be a green halo surrounding the lesion. False melanose lesions:False melanose lesions are characterised by a large number of tiny, tan, slightly elevated lesions. With an average diameter of less than 1 mm, the lesions are significantly smaller than the hard spot kind.Later in the season, it can be challenging to watch them because they are found on immature fruit. There are no pycnidia, unlike hard spot lesions. Cracked spot lesions:Lesions known as "cracked spots" can appear on both ripe and unripe fruit. Large, slightly elevated, dark brown dots characterise them. Later in the season, it may be challenging to discern the elevated fractures they produce on the fruit's surface. Freckle spot lesions: The early stage of virulent spot lesions is freckle spot lesions. They have a variety of pycnidia and are tiny, reddish, and irregularly shaped. Due to their presence on mature fruit and during post-harvest storage, these lesions are most visible at the end of the season. Virulent spot lesions: Freckle spot lesions in their full condition can be seen on mature fruit and during post-harvest storage. They resemble freckle spot lesions in appearance but can cover the entire fruit in conditions of extreme humidity. The immediate harm to the fruit caused by this type of lesion can be disastrous economically. On extremely vulnerable citrus cultivars, like lemons, as well as in improperly managed orchards, leaf symptoms are typically seen. After the leaves have died, hidden infections typically cause the symptoms to appear. Pin-point reddish-brown spots may grow into bigger, cirrhotic lesions that have grey centres and reddish or brown edges. Fungicides like copper and/or strobilurins should be sprayed monthly from early May to mid-September (in the northern hemisphere) to manage Guignardia citriparpa. Accelerating the decomposition of leaf litter beneath the trees in citrus groves is another means of control. Accelerating this decay lessens the possibility of ascospore inoculation, which typically occurs in the middle of March. Three techniques could be used to speed up this breakdown. One strategy is to boost the grove's microsprinkler irrigation to 30 minutes per day, at least five days per week. For around one and a half months, this type of control should be used. Applying urea or ammonium to the leaf litter is the second technique. Application of lime or calcium carbonate to the litter is the last and most effective way to hasten leaf decomposition. The production of spores and the number of fungal structures are decreased by urea, lime, and calcium carbonate.Since the fungus needs moisture to grow, the citrus grove's air flow should be increased to lessen leaf wetness. Along with these techniques, it's critical to remove waste materials like twigs and fallen fruit in a way that lessens the risk of spreading disease to neighbouring plants. On decomposing twigs, Citrus Black Spot can colonise and breed. Citrus waste should be burned for at least two hours at a minimum temperature of 180 °F, buried in a landfill, fed to animals, or cremated. Moving plant waste should only be done carefully to prevent the spread of infectious ascospores. Citrus black spot-affected trees need to be taken out of the grove and disposed of. These trees need to be cut down since they frequently blossom out of season when they are stressed and deteriorating. When there are fruits of different ages on the same tree, it is feasible for the asexual spores on the older fruits to spread to the younger fruits, worsening the disease. Fruits should be collected before blooming because Valencia orange off-season flowering is frequently more difficult when old and new crops coincide.

CITRUS CANKER

The bacterium Xanthomonas (X. axonopodis; X. campestris) causes the illness citrus canker, which affects species of citrus. On the leaves, stems, and fruit of citrus trees, such as lime, orange, and grapefruit, infection results in lesions. Although not hazardous to people, canker has a severe negative impact on citrus trees' health, causing leaves and fruit to fall off before they should. Canker-infected fruit is safe to eat but too unattractive to be marketed. Citrus canker is mostly a leaf spot and rind blemishing disease, but in exceptionally favourable circumstances, it can also result in fruit drop, shoot dieback, and defoliation.The illness, which is thought to have its origins in Southeast Asia, is quite persistent once it has spread throughout a region. Groves of citrus trees have been cut down in an effort to eradicate the disease. Canker outbreaks are a problem in nations like Brazil and the US. Citrus canker-infected plants develop distinctive lesions on leaves, stems, and fruit that have elevated, brown, water-soaked borders and frequently have a yellow halo or ring effect surrounding them. Older lesions appear corky and frequently still have the halo effect. The bacterium spreads through wounds on fruit, stems, and leaves. The lesions exude bacteria that, when spread by wind-driven rain, can infect nearby plants. Hurricanes may accelerate the spread of an infection. Additionally, contaminated tools and the movement of sick or seemingly healthy plants can spread the disease. A plant may appear to be healthy yet actually be sick because of the disease's latency. Bacteria that cause citrus canker can enter through a plant's stomata, wounds on leaves, or other green areas of the plant. Younger leaves are typically thought to be the most vulnerable. Additionally, the Phyllocnistis citrella larvae that cause harm to citrus leaves might harbour infectious organisms. Within 14 days of the inoculation into a vulnerable host in a controlled laboratory environment, symptoms may start to manifest. It may take several months after infection for symptoms to manifest in the field setting and be easily distinguished from those of other foliar diseases. The latency of the disease is increased by lower temperatures. In older lesions and on other plant surfaces, citrus canker bacteria can survive for several months. older lesions and on other plant surfaces, citrus canker bacteria can survive for several months.

To stop the spread of X. axonopodis, quarantine measures are put in place in places where citrus canker is not endemic or has been eradicated. On the other hand, Integrated Pest Management (IPM) is used in areas where citrus canker develops. The conversion of vulnerable citrus plants to cultivars of citrus that are robust to field conditions is the most noticeable aspect of this management programme. Numerous steps are done to prevent citrus canker from ruining a harvest in addition to employing resistant varieties in the fields. Exclusion, eradication, and sanitation are the three broad categories into which the methods can be separated. Exclusion: Fruits or citrus trees imported from abroad are examined to make sure they are clear of bacteria. The cultivation of XAC (X. axonopodis pv. citri)-free nursery trees for the exclusion of canker from orchards is also required under the management programme. Strict regulations on the importation of citrus are put in place in countries that cultivate citrus since the germs can be imported from nations with endemic canker or canker outbreaks. Only canker-free fields, at least a year following effective eradication, will be used to plant citrus trees. Additionally, planting locations are chosen to reduce conditions that could help X. axonopodis spread. For instance, places with strong winds are avoided to reduce the spread of bacterial inoculum to citrus trees that are vulnerable to it. Eradication Once citrus canker has been introduced to a field, eradication of the diseased trees is necessary to stop the bacteria's spread. For instance, between 2000 and 2006, all citrus trees in Florida had to be removed if they were within 1,900 feet (580 m) of diseased trees. As the bacteria can persist on the lesions of wooden branches for years, the infected trees are uprooted and burned throughout the operation. The trees are felled, chipped, and dumped in landfills in urban areas. operation. The trees are felled, chipped, and dumped in landfills in urban areas. Sanitation X. axonopodis pv. citri can spread mechanically through people and equipment. In order to avoid the spread of infection from the affected areas, citrus orchard workers are required to perform thorough cleaning of personnel and equipment. Wet foliage in the bacterial dispersal zone can become infected by aerosol inoculum. Getting in contact with the moist leaves can potentially pollute vehicles. Spraying a bactericide on contaminated machinery and equipment can disinfect them.

CITRUS SCAB

Citrus scab, which is brought on by the fungus Elsinoe fawcetti and can affect all citrus species, is economically significant for the production of lemons, Temples, Murcott, Page, Minneola tangelos, and, in certain cases, grapefruit. Additionally, citrus scab on the foliage and shoots stunts the growth of the rough lemon, sour orange, Carizzo citranage, trifoliate orange, and Rangpur lime plants grown from seedling rootstocks. Compared to groves planted on a ridge, those situated in flatwoods typically have more severe scab. Scab is a rare occurrence on sweet orange fruit. Trees are typically only afflicted by the sweet orange blight if they are located extremely close to other infected trees. On leaves, fruit, stems, bloom pedicels (flower stalks), and buttons, symptoms appear. The most vulnerable tissue is young tissue, therefore check the most recent growth for signs. Fruit and leaves may show signs of scab four and seven days after infection, respectively. Leaf symptoms initially appear as little circular protrusions on either side of developing leaves. These bumps develop into projections that are cream to yellow-orange at the tips a few days after these early symptoms. These projections take on a cone-like structure as leaves grow.Corresponding depressions on the leaf are seen on the other side.Infected leaves that are severely deformed. Fruit symptoms are elevated, abnormal growths on the rind that range in colour from white to buff. The scabby regions appear at the tip of blister-shaped protrusions on the rind of tangelos, lemons, and sour oranges. The blister effect is less noticeable on grapefruit, where it generally takes the form of flattened scabby sheets. Later, these sore spots could develop cracks. Fruit that has been severely harmed may fall off the tree. Citrus scab is mostly a cosmetic issue that affects fruit used for fresh market sales, but on kinds that are particularly vulnerable (such Temples), the damage can be severe enough to affect fruit production for processing as well. Scab is significant in seedbeds on vulnerable rootstocks and results in stunting of seedlings. A situation where scab treatment may be necessary on scion kinds in the nursery may arise due to excessive irrigation since leaves on all citrus varieties, with the exception of sweet orange, are susceptible. Controlling citrus scab is essential, especially for some citrus cultivars going into the fresh market. For the prevention of scab, routine, preventative fungicide treatments are required for Minneola tangelos, Murcotts, Temples, Page, and lemons. Only areas of grapefruit groves where scab has previously occurred should be treated with a fungicide. The timing of fungicide applications is intended to limit spore generation while the spring growth flush and newly set fruit are vulnerable. This can be done by applying fungicides at late dormancy, at bloom, or immediately after. Furthermore, some fungicides, like Difolatan (no longer available), have a lengthy residual effect and are redistributed, preventing infection on leaves or fruit that have grown after spraying. A single fungicide application at bloom may be sufficient in circumstances with minimal disease pressure, such as those where scab was previously mild in intensity. Two fungicide applications may be required in areas with significant disease pressure, such as groves where severe scab has previously occurred or where spring rains have been plentiful. The first spray should be made when the plant is in its late dormant state, just before anticipated shoot growth, and the second application should be made four to six weeks later, typically at bloom or soon after petal fall. Control measures based on culture will lessen the severity of scabs. During the crucial first two to three weeks of spring sprout emergence, overhead irrigation should be reduced or, if feasible, avoided entirely. Keep in mind that this fungus can only infect leaf tissue of susceptible kinds up to the point where it has reached 1/4 of its final width.

CITRUS GREENING


A pathogen conveyed by a vector is the cause of the citrus illness known as citrus greening disease. Liberibacter spp., which are mobile bacteria, are the culprits. The African citrus psyllid Trioza erytreae, commonly known as the two-spotted citrus psyllid, and the Asian citrus psyllid Diaphorina citri are the carriers and transmitters of the disease. It has no known treatment. Furthermore, it has been proven to be graft-transmissible. There are now three known types of HLB: the heat-tolerant Asian form, the heat-sensitive African form, and the heat-sensitive American form. The illness was initially identified in 1929, and it was first identified in China in 1943. Common symptoms of citrus greening include yellowing of the veins and surrounding tissues. These symptoms are followed by mottling of the entire leaf, early defoliation, dieback of twigs, decay of feeder rootlets and lateral roots, and a decline in vigour, which is ultimately followed by the death of the entire plant. Affected trees exhibit stunted growth, numerous off-season blossoms that, for the most part, fall off, and small, atypically shaped fruit with a thick, pale skin that is still green at the bottom and has a bitter flavour. Common symptoms can sometimes be confused with nutritional deficiencies; however, the pattern of symmetry helps to distinguish between vitamin deficits. While citrus greening has an uneven yellowing around the vein, nutritional deficits typically exhibit symmetry along the leaf vein margin. Greening and stunting of the fruit, especially after maturity, are the most obvious signs of citrus greening. Treatment for citrus greening including applying antibiotics, peptides and using cover crops strategy.

CITRUS MELANOSE

When the tissues grow and expand over a lengthy period of rainy or humid weather, the melanose disease can harm immature leaves and fruits of several citrus species or variations. The signs of this widespread fungal illness range from tiny lesions that resemble scabs or patches to damage patterns known as tear-drop, mudcake, and star melanose. Diaporthe citri, a plant-pathogenic fungus, is the culprit behind citrus melanose. Although it can cause significant fruit rind discolorations, the fungus often has no effect on the pulp. The small, elevated, black blemishes on leaves are frequently encircled by yellow haloes and might deform the leaf. On leaves that have not fully grown, infections develop. After leaf infection, dark-colored, elevated, corky pustules develop. Yellowed leaf tissue or yellow halo may surround the pustules. Later, the golden hue might change to green. Shoot apices that have been severely diseased may change shape or start to die. Mature leaves that have fully grown resist infection. On fruits, illness manifests as variously sized, darkly coloured pustules that are typically elevated. The pustules may combine to make mudcake melanose, which has a broken look, or they may spread across the fruit's surface as a result of streaming water to provide tear-stain symptoms. When the pathogen infects extremely young fruits, pustules may get greater in size. Tendrils of spores are a symptom of the disease. Melanose disease care may not be necessary if fruits are cultivated for juicing or other processing because the condition may not have a significant influence on fruit yield. Pruning. Trim away dead branches on a regular basis. This will boost air circulation to dry out the canopy, lower pathogen survivability, and make it possible for fungicides to penetrate and coat the foliage more effectively. Fungicides. For the treatment of diseases, fungicide sprays to immature fruits and foliage may be required. Frequent fungicide applications may be necessary in areas where the disease has a tendency to be severe. The most widely used fungicides worldwide are made of copper. Citrus fruits may experience star melanose signs after copper spray application that are distinct from those seen on unsprayed fruits. Melanose disease damage to citrus rinds cannot be reduced by post-harvest treatments or fruit storage conditions the citrus kind. In locations with heavy rainfall, avoid planting citrus species or cultivars that are extremely vulnerable (such as sweet orange, grapefruit, or pummelo). selection of the planting site: Citrus trees should be planted in areas with little rain. cropping procedure: Interplant citrus with hosts that are resistant to it and avoid monocultures. Sanitation: Plant debris that has fallen from the citrus canopy should be picked up and destroyed.

8 Experimentation and Results

8.1 Experimentation

The suggested technique classifies citrus diseases into distinct groups using a cutting-edge CNN model, including Black spot, canker, scab, greening, and Melanose. It incorporates a suitable number of layers in the suggested deep learning model and compares the effciency of the suggested model to that of similar research, exhibiting better performance. The proposed CNN model is an image feature separator that automatically extracts features. A pixel vector technique loses a lot of connectivity between pixels, whereas a CNN effectively down samples the image via convolution and then employs a predictive layer at the end.

TABLE 8. CNN models' micro and macro metrics (%) for each class of citrus-fruit-leaves (diseased and healthy).

Model for citrus disease	Macro Precision (%)	Micro Precision (%)	Macro Recall (%)	Micro Recall (%)	Macro F-score (%)	Micro F-measure (%)
CNN-citrus-disease (1)	0.74	0.75	0.84	0.75	0.79	0.75
CNN-citrus-disease (2)	0.74	0.76	0.86	0.76	0.79	0.76
CNN-citrus-disease (3)	0.62	0.82	0.85	0.82	0.72	0.82
CNN-citrus-disease (4)	0.76	0.87	0.88	0.87	0.82	0.87
CNN-citrus-disease (5)	0.90	0.90	0.90	0.90	0.90	0.90
CNN-citrus-disease (6)	0.88	0.91	0.94	0.91	0.91	0.90
CNN-citrus-disease (7)	0.93	0.94	0.93	0.93	0.92	0.93
CNN-citrus-disease (8)	0.97	0.96	0.97	0.96	0.96	0.96
CNN-citrus-disease (9)	0.96	0.97	0.96	0.97	0.96	0.97
CNN-citrus-disease (10)	0.98	0.99	0.98	0.99	0.98	0.99

8.2 Results

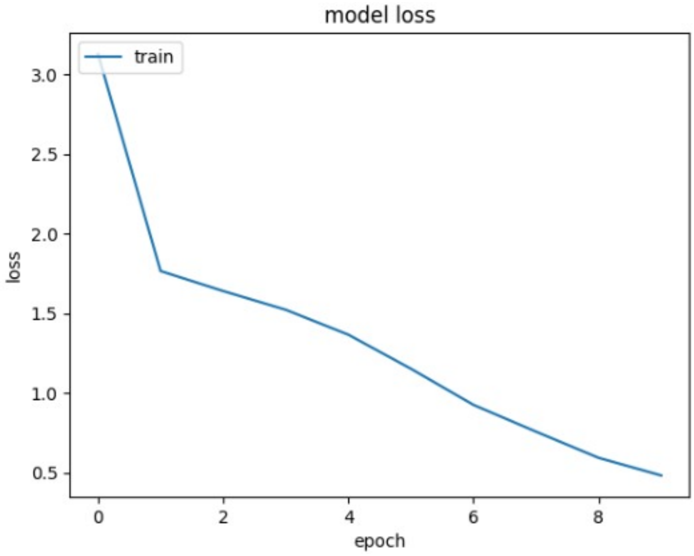
Model Name	Model Loss	Model Accuracy
Basic Model	48.19	94.54
VGG-16	2.46	99.66
VGG-19	6.48	98.34
MobileNet	2.96	99.66
InceptionV3	3.47	99.66

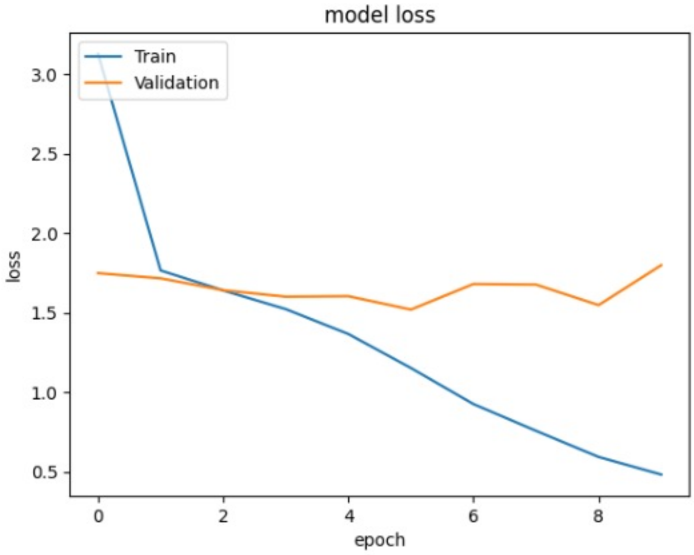
The CNN model successfully captures complementary discriminative properties by combining many layers. On the Citrus and PlantVillage datasets, we contrasted the CNN model with various state-of-the-art deep learning techniques to assess its performance. The testing data showed that the CNN model outperformed its competitors on a number of different metrics.In contrast to the CNN model, the Support Vector Machine model performed poorly and had a low accuracy rate. As a result, the CNN model produced excellent classification results, making it a potential method for identifying diseases in citrus fruits and leaves.

Five modules make up the suggested version for identifying affected areas and different phases of citrus fruit illnesses' severity. Gathering photos, applying expert knowledge for labelling, performing object recognition and segmentation, extracting feature maps using transfer learning-based CNN networks, and determining disease severity using multi-class sequential CNN are all successfully accomplished by the approach. On images chosen at random, the algorithm's accuracy was assessed, yielding impressive findings of 96 percent for healthy, 99 percent for low degree, 98 percent for excessive degree, and 97 percent for moderate stages of the condition.

The suggested Using a single stream convolutional neural network architecture, citrus fruit illnesses may be categorised. The architecture uses operations like brightness enhancement and contrast correction to augment data in order to expand the training samples. Transfer learning and enhanced dataset training are used to use the MobileNet-V2 CNN model. The Whale Optimisation Algorithm is used to extract deep features and eliminate unnecessary data. Selected characteristics are used for classification as opposed to other classifiers such the Gaussian Naive Bayes, linear SVM, quadratic SVM, and fine tree. In terms of speed and accuracy, the suggested architecture fared better than alternatives. The results show that feature selection can increase learning capacity, shorten computation time, and maintain accuracy.

Inception With multiple layers trained to capture low-level traits, mid-level features, and precision-level illness diagnosis, the ResNet V2 model was utilised to extract features. In order to increase the filter bank dimension, a filter expansion layer was added. This technique worked well at obtaining useful features for citrus fruit and leaf disease identification.selection.





9 Conclusion

In conclusion, our CNN-based model for identifying good and diseased citrus fruits and leaves efficiently distinguishes between them. The model successfully extracts both low-level and high-level features from the images by using two convolutional layers. This enables accurate categorization into classes like healthy, greening, canker, scab, Blackspot, and Melanose. Our model uses deep learning to automate feature extraction from beginning to end, doing away with the necessity for manually created features. Our CNN model provides a simplified and effective way for disease classification in citrus fruits and leaves, as opposed to conventional image processing techniques that demand numerous stages and manual feature engineering. The capacity of the algorithm to distinguish between healthy and unhealthy samples offers important insights for agricultural practises. Additionally, our algorithm extends beyond disease detection and recommends suitable fertilisers to lessen the effects of particular illnesses seen in citrus fruits or leaves. The practicality and usefulness of our suggested solution in the agricultural sector are improved by this all-encompassing approach. We have created a reliable framework for identifying citrus fruit/leaf diseases through the gathering, compilation, and use of data along with our CNN model. Our model produces precise and dependable findings by utilising deep learning, enabling quick actions and interventions for disease management in citrus crops. Our suggested CNN model's classification performance is encouraging, offering a good basis for further study and advancements in disease detection and prevention in the citrus industry. Our model can help farmers and researchers better monitor and treat diseases in citrus plants thanks to ongoing developments in deep learning and image analysis methods. In conclusion, our CNN-based method provides a thorough and effective remedy for citrus fruit and leaf disease identification.

10 Future Enhancement

In future enhancements, we envision several opportunities to further improve and expand upon our proposed CNN-based leaf disease identification model for citrus fruits and leaves. These include: Utilizing additional plant disease datasets of varying sizes to enhance the model's performance and robustness. Incorporating diverse datasets can help capture a wider range of disease patterns and increase the model's ability to generalize across different scenarios. Exploring the application of various deep learning models such as RNN, LSTM, Bi-LSTM, and hybrid models like CNN + LSTM or CNN + RNN. By leveraging these advanced architectures, we can potentially uncover new insights and improve the accuracy of disease classification. Considering the inclusion of additional disease classes for more fine-grained analysis. While our current model focuses on five disease categories, expanding the classification framework to accommodate a broader range of diseases would enable more comprehensive disease diagnosis and monitoring. Developing and implementing a precision farming framework based on the Internet of Things (IoT). Integrating IoT technologies into our model can enable real-time monitoring of plant health, incorporating environmental data, and facilitating timely interventions for disease management. By pursuing these future enhancements, we aim to continuously enhance the performance, versatility, and applicability of our CNN-based leaf disease identification model in the context of citrus farming and beyond. These advancements have the potential to contribute significantly to the field of agriculture, aiding farmers in making informed decisions and promoting sustainable crop production.

11 References

W. Gomez-Flores, J. Jose Garza-Saldana, “A Huanglongbing Detection Method for Orange Trees Based on Deep Neural Networks and Transfer Learning” IEEE Access, 4 November 2022.

[2] M. Hassam, M. Attique Khani, “A Single Stream Modified MobileNet V2 Whale Controlled Entropy Based Optimization Framework for Citrus Fruit Diseases Recognition” IEEE access, 24 August 2022.

[3] W. Pan, J. Qin: “A Smart Mobile Diagnosis System for Citrus Diseases Based on Densely Connected Convolutional Networks” IEEE Access Volume 7, 26 June 2019.

[4] C. Senthilkumar, M. Kamarasan: “An Effective Citrus Disease Detection and Classification Using Deep Learning Based Inception Resnet V2 Model” Turkish Journal of Computer and Mathematics Education Vol.12 No.12 (2021), 2283-2296 Research Article 23 May 2021.

[5]S. Farhana Syed-Ab-Rahman, “Citrus disease detection and classification using end-to-end anchor-based deep learning model ” Accepted: 20 April 2021

[6]A. Kumar Sainia , R. Bhatnagar: “ Detection and Classification Techniques of Citrus Leaves Diseases: A Survey” Turkish Journal of Computer and Mathematics Education Vol.12 No.6 (2021)

[7]S. Janarthan, S. Tuseethan, John Yearwood: “Deep metric Learning Based Citrus Disease Classification with Sparse Data that was published on September 3,2020 IEEE Access

[8]P. Dhiman, V.Kukreja, P. Manoharan,A. Kaur,M.M. Kamruzzaman,: “A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits” Received: 29 December 2021 Accepted: 4 February 2022 Published: 8 February 2022

[9] M. Zhang, S. Liu , F. Yang , and J. Liu : “Classification of Canker on Small Datasets Using Improved Deep Convolutional Generative Adversarial Networks” IEEE Access, date of current version April 24, 2019.

[10] X. Liu , Y. Hu , G. Zhou, Weiwei Cai , “DS-MENet for the classification of citrus disease” Published 22 July 2022.

[11] G. W. Lindsay: “Convolutional neural networks as a model of the visual system: Past, present, and future,” J. Cognit. Neurosci., vol. 33, no. 10, pp. 2017–2031, Sep. 2021

[12] A. Kamilaris and F. X. Prenafeta-Boldú: “Deep learning in agriculture: A survey,” Comput. Electron. Agricult., vol. 147,pp.70–90, Aug. 2018.

[13] C. Shorten, T. M. Khoshgoftaar: “A survey on image data augmentation for deep learning,” J. Big Data, vol. 6, Dec 2019.

[14] M. Sandler, A. Howard, M. Zhu, “MobileNetV2: Inverted residuals and linear bottlenecks,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2018.

[15] K. Dong, C. Zhou, “MobileNetV2 model for image classification,” in Proc. 2nd Int. Conf. Inf. Technol. Comput. Appl. (ITCA), Dec. 2020.

[16] G. Huang, Z. Liu, L. van der Maaten, ‘Densely connected convolutional networks,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jul. 2017.

[17] G., Huang, Wang. Y, Zhi, R.: “Contrast enhancement of brightness-distorted images by improved adaptive gamma correction.” Computers Electrical Engineering,2018.

[18] S Ren, K He, Girshick R: “Faster r-cnn: towards real-time object detection with region proposal networks.” IEEE Trans Pattern Anal Mach Intell 2016.

[19] MH Hesamian, W Jia, “Deep learning techniques for medical image segmentation: Achievements and challenges.” ,2019, J Digit Imaging 32(4):582–596

[20] B. S. Prajapati, V. K Dabhi.: “A survey on detection and classification of cotton leaf diseases. International conference on Electrical, Electronics, and Optimization Techniques,” ICEEOT 2016, 2499–2506