ANALYSIS OF COTTON PLANT DISEASE DETECTION USING DEEP LEARNING METHODS

Project Report
Submitted in Partial Fulfilment of the Requirements
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In
Signal Processing and Digital Design

by

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CANDIDATE’S DECLARATION

I, Himani Bhatheja, Roll No. 2K19/SPD/06 student of M.Tech (Signal Processing and Digital Design), hereby declare that the project titled “**Analysis of Cotton Plant Disease Detection Using Deep Learning Methods**” which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associate ship, Fellowship or other similar title or recognition.

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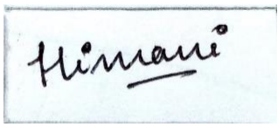
Date: 31/10/2021 2K19/SPD/06



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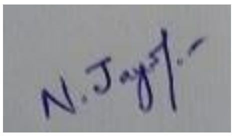
<u>CERTIFICATE</u>

I hereby certify that the Project Dissertation titled "**Analysis of Cotton Plant Disease Detection Using Deep Learning Methods**" which is submitted by Himani Bhatheja, Roll No. 2K19/SPD/06, Electronics and Communication Engineering Department, Delhi Technological University, Delhi, in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree to this University or elsewhere.



Place: Delhi

Date: 09/11/2021

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ABSTRACT

Disease detection in agriculture has become very crucial in today's deteriorating climatic conditions. Cotton production plays a vital role in our country's economy for being a major cotton producer in the world. Monitoring the large cotton fields manually becomes a tiresome activity for farmers. To leverage advancements in technology, deep learning and image processing techniques are being used for identification of diseases in crops at an early stage and thus preventing them from further harm. In this work, we have done analysis of transfer learning techniques for disease detection and proposed a deep convolutional neural network for accurate classification of fresh and diseased plants. The proposed model gives better accuracy and performs faster than pre-trained models like VGG16, ResNet50, ResNet152V2, InceptionV3 and EfficientNet-B0. Various data augmentation methods were used to improve the training process and reduce chances of overfitting. Fine tuning methods were also implemented on InceptionV3 and EfficientNet-B0 along with data augmentation. A detailed analysis of all the techniques used is done for better understanding of transfer learning techniques along with different aspects like fine tuning and data augmentation. For comparison, the analysis of performance of a model built from scratch by adding convolutional, max pooling and fully connected layers is also done, which gave training accuracy of 94.52%, validation accuracy of 96.88% and test accuracy of 98.11%. Apart from that, it took approximately 50% less time in implementation. So, monitoring of large fields can be done using the proposed model for early diagnosis and treatment for better production.

ACKNOWLEDGEMENT

I would like to express my gratitude towards all the people who have contributed their precious time and effort to help me without whom it would not have been possible for me to understand and complete the project.

With profound sense of gratitude, I would like to thank Dr. N. Jayanthi, my Project guide, for her guidance, patience, support and encouragement throughout the period this work was carried out. Her readiness for consultation at all times, her educative comments, her concern and assistance even with practical things have been invaluable.

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CHAPTER 1

INTRODUCTION

Agriculture is a very important part of any country's growth and economy, so it becomes very important to consider the quality of crop production and supervise the crop growth. Cotton production is of vital importance to India because of being one of the largest producers in the world accounting to almost 26% of the entire cotton production [17]. Cotton crops can suffer from several diseases like Cercospora, Bacterial blight, Ascochyta blight, and Target spot. Thus, identifying these diseases at an early time becomes crucial for farmers to produce a healthy productive harvest. Therefore, modern technologies for detection of plant diseases are being used to help farmers in monitoring of crops. One such technique is Deep Learning. It is more hierarchically complex and abstracted than machine learning.

For feasible agriculture, technological advancements can be leveraged for automating detection of diseases. There are several factors that can affect the crop's health, such as moisture, pathogens, temperature invariability, strong winds, soil quality etc. The input dataset, which is used in our research work, therefore, has images from open fields of cotton crop with varying background, size and sunlight conditions. Also, the dataset has plant images as well as leaf images to classify the diseased crop and fresh crop.

This research work intends to utilize Deep convolutional neural network which is built from scratch by adding convolutional layers and compares it with well renowned pre-trained CNN architectures - ResNet with 50 and 152 layers, VGG16, EfficientNet and Inception-V3 for classification of diseased cotton plant images using transfer learning. The method of using pre-trained deep CNN neural network for a new set of problem and feature extraction with change in last few layers is known as Transfer Learning.

Modern technologies and advancement can give the famers a means to prevent damage happening to their crops. Generally, conventional machine learning algorithms such as K-means clustering and support vector machine have complex image processing and feature extraction methods, which reduces the accuracy of disease identification. These techniques are better suited for the detection of plant images in consistent background which have been performed in a consummate lab condition [1]. There have been various advancements in research in the Deep Learning field to predict diseases at an early stage in the cotton plants and leaves. For example, Transfer Learning which is very useful in the field of Computer Vision, Image Processing and Natural Language Processing particularly due to following reasons:

- It needs less training data
- It helps models generalizes better
- It makes training easier to debug

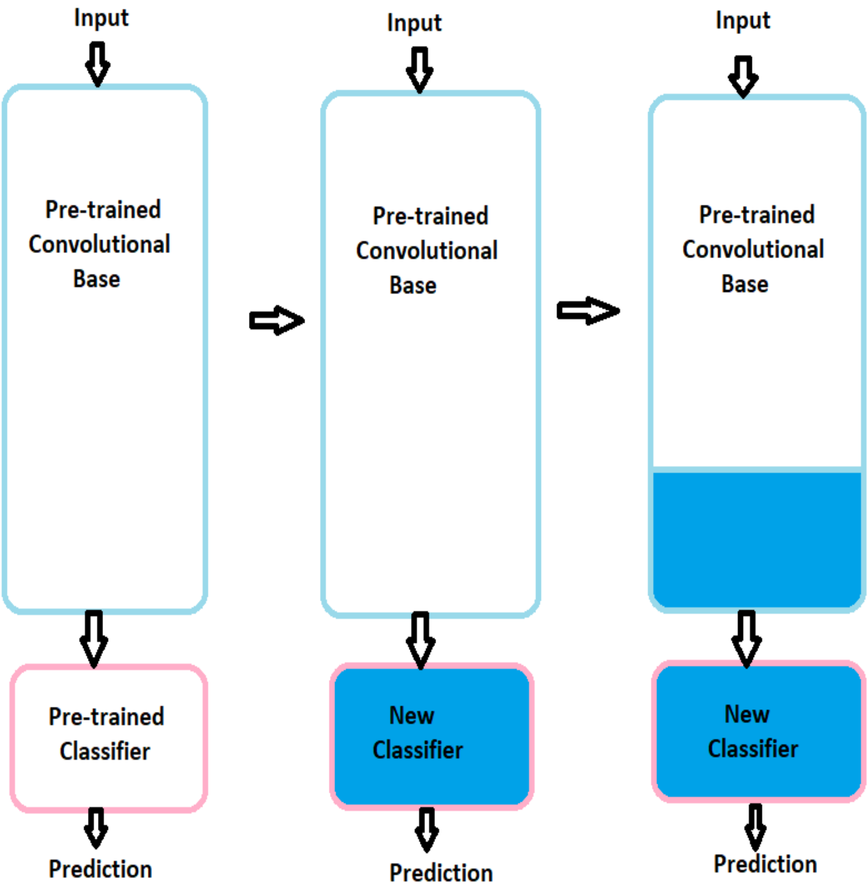


Fig. 1.1 Understanding Transfer Learning

Transfer Learning technique is essentially a sum of Convolutional neural networks designed, which is actually giving state-of-the-art algorithm to classify different kinds of images. Every year ImageNet Classification competition is held where people design a new convolutional neural network to classify different images of 1000s of objects. Then, the one with the highest accuracy will be given the price money and will be treated as the state-of-the-art model. Some of the really good algorithms that are designed and are used for classification problem are as follows: Xception, VGG 16, VGG 19, ResNet50, ResNet101, InceptionV3, ResNet152V2, Inception-ResNetV2, MobileNet, EfficientNet, DenseNet. The proposed work consists of analysis of five of these models and a Deep CNN which is built from scratch. Cotton disease dataset is used for the training purpose and insights drawn from implementation of these models and testing them on unseen data are given in the end.

CHAPTER 2

LITERATURE REVIEW

While going through the current research work, it was observed that two types of detection can be opted – based on machine learning and image processing, and based on deep learning and transfer learning.

2.1 Based on Machine Learning and Image Processing:

A research paper [1] that develops an Apple Leaf Diseases Classifier in real time uses a combination of deep-CNNs by proposing the GoogLeNet Inception network along with Alex Precursor and Cascade Inception architecture to perform the classification of diseased apple leaves dataset. This paper also gives a comparative analysis between their own model and previously advanced models like SVM, back propagation (BP) Neural Net, ResNet-20, AlexNet and VGG Network 16. The metrics that were used in this paper were accuracy, performance, convergence rate and the computational resources that are required. These architectures were tested on the basis of above stated metrics. The dataset used was Apple Leaf Disease Dataset (ALDD), and these criteria were tested on the dataset that comprised of nearly 1053 images. The built classifier was tested on the dataset and accuracy for that came out to be 97.62%.

Geetharamani G. et. al. [10] proposed a novel model for detection of plant leaf disease which also included six kinds of data augmentation techniques like noise injection, gamma correction, principal component analysis color augmentation, scaling, rotation and flip. The performance of proposed model was rigorously compared with machine algorithms like support vector machine, decision tree, logistic regression and k-nearest neighbors (KNN). Training was done on Plant leaves dataset and the proposed deep CNN model achieved accuracy of 96.46% for classification of 38 different classes.

Jian-hua ZHANG et. al. in [11] used automated segmentation model including active gradient and local information to enhance performance of segmentation of images of cotton leaves. The model used could segment the cotton leaves with uneven lighting, shadow, leaf disease spot blur, staggered condition, unclear diseased leaf edges, adhesive diseased leaf and complex background. A comparative analysis for all seven types of images was conducted between Geodesic Active Contour (GAC) algorithm, Local Binary Fitting (LBF) algorithm, Chan-Vese (C-V) algorithm and the proposed algorithm. The advantages of this model include accuracy in segmentation and running time in processing 7 types of diseased cotton leaves images.

Rafael Faria Caldeira et. al. [15] used deep neural network models ResNet50 and GoogleNet for transfer learning on Cotton leaves dataset. Testing of four traditional machine learning models such as Artificial neural network (ANN), Support Vector Machine (SVM), Hybrid Neuro-Fuzzy networks (NFC) and Closest k-neighbors (KNN) was done in comparison to new transfer learning models. The deep CNN based transfer learning models performed with 25% more precision than machine learning algorithms. Among the CNN based models, ResNet50 performed better than GoogleNet, although the technical difference of performance was insignificant according to authors.

Zhenping Qiang et. al. [16] proposed fine tuning based Inception V3 transfer learning method on PlantVillage dataset. They obtained results for various batch sizes and learning rate that best suited the detection. The base model layers were frozen and three-layer neural network layer added from bottleneck node to perform fine-tuning. They obtained a highest test set precision of 93% for batch size 100 and learning rate 0.01.

2.2 Based on Deep Learning and Transfer Learning:

In paper [8], the authors used VGG16 and ResNet50 as transfer learning models and compared them with Multi-layered Convolutional Neural Network (MCNN) on Potato, tomato and corn plant images. The PlantVillage dataset was used for collecting the data and the classification was done for tomato, potato and corn. Out of the three, MCNN was 93.70% accurate, VGG16 had 98.30% accuracy and ResNet50 attained highest accuracy of 98.70%.

In [13], the authors introduced EfficientNet deep CNN model for disease detection in plant leaves which was also compared with other state-of-the-art convolutional neural network models using transfer learning technique. Both the original dataset and augmented dataset of PlantVillage dataset were fed to these models for training. While using transfer learning, all the layers of these pre-trained models were used for training purpose. The EfficientNet B4 model achieved highest accuracy amongst other models for augmented image dataset with 99.91%, and the EfficientNet B5 performed well for original dataset with accuracy of 99.91%.

J. Chen et. al. [4] used VGGNet pre-trained on the ImageNet and Inception modules by using pre-trained weights. A network generated by replacement layers consisted of pre-trained layers that was used in feature extraction and an additional structure which is used for the purpose of classification. They achieved a validation accuracy of 91.83% on publically available dataset.

The paper [5] describes a comparative study on different transfer learning architectures without Data augmentation. The dataset used was PlantVillage with 14 types of plant leaf images. The authors mentioned that DenseNet has ability to improve the accuracy with increasing number of epochs without overfitting and deteriorating the performance. Finally, the test accuracy of DenseNet was 99.75% with a drawback of large computational time.

In the paper [6], the authors have used a model that has convolution and max pooling layers are used following 2 fully connected layers on Tomato plant disease dataset. They implemented various filtering techniques in each layer and used data augmentation for balancing the images inside each class. The test accuracy ranged between 76% to 100% and average testing accuracy is 91.2%.

Wang et. al. [7] used deep CNN on PlantVillage dataset to identify the disease complexity in apple rot images of 4 severity stages. They evaluated the performance of deep and shallow network models. Finally, it was mentioned that deep VGG16 model is best that provided accuracy of 90.4%.

CHAPTER 3

METHODOLOGY

The Convolutional Neural Networks consists of multiple layers: convolutional, pooling and fully connected layers, in which the first two layers are used for extracting features from input images and last layer is used for classification [10]. Pooling layer is used to decrease the dimensionality of extracted attributes. Softmax is used with the fully connected layer to perform the classification.

In this research work, we have opted two paths: first one is using pre-trained architectures as feature extractors and changing the last layers to make use of transfer learning, second one is by developing a deep convolutional neural network by adding different convolutional, batch normalization, max pooling, dense and flatten layers

The entire method of detection using a model is a step-by-step process devised into a number of stages that are:

3.1 Data Acquisition and Pre-processing

As the cotton plant is majorly grown in areas of Western India like Gujarat, Maharashtra and Karnataka, so to collect the images of cotton plants we referred the internet. The dataset was taken from the Cotton Disease database with images of healthy cotton plants and leaves, and diseased cotton plants and leaves. The Fig. 3.1 describes the different types of input images in the dataset. Diseases like white spots, bacterial blight, leaf sucking and chewing pests, grey mildew, Myrothecium leaf spot, Cercospora leaf spot, etc. affect the cotton crops adversely.

This dataset has examples of leaf sucking pests such as Aphids - affected plants in the diseased cotton plants class, and white spots on leaves in the diseased leaves class – which happens because of excessive use of herbicides and pesticides which can affect cotton production and even death in plants. Fresh plant and leaves images are present in the cotton fresh plant and cotton fresh leaves categories. In fig. 3.1, the first image is of diseased leaf with white spots on it, the second image is of a diseased plant which is suffering from leaf sucking pest, the third one is of a fresh leaf and last one is of a fresh plant with no diseases.

To increase the training efficiency of the model, we implemented data augmentation techniques on training set for generating extra images from existing input images by rescaling, rotating, shifting width, shifting height, and applying zoom, shear and horizontal flip. On validation set and test set, only scaling and resizing of images is done to maintain uniformity in the dataset.

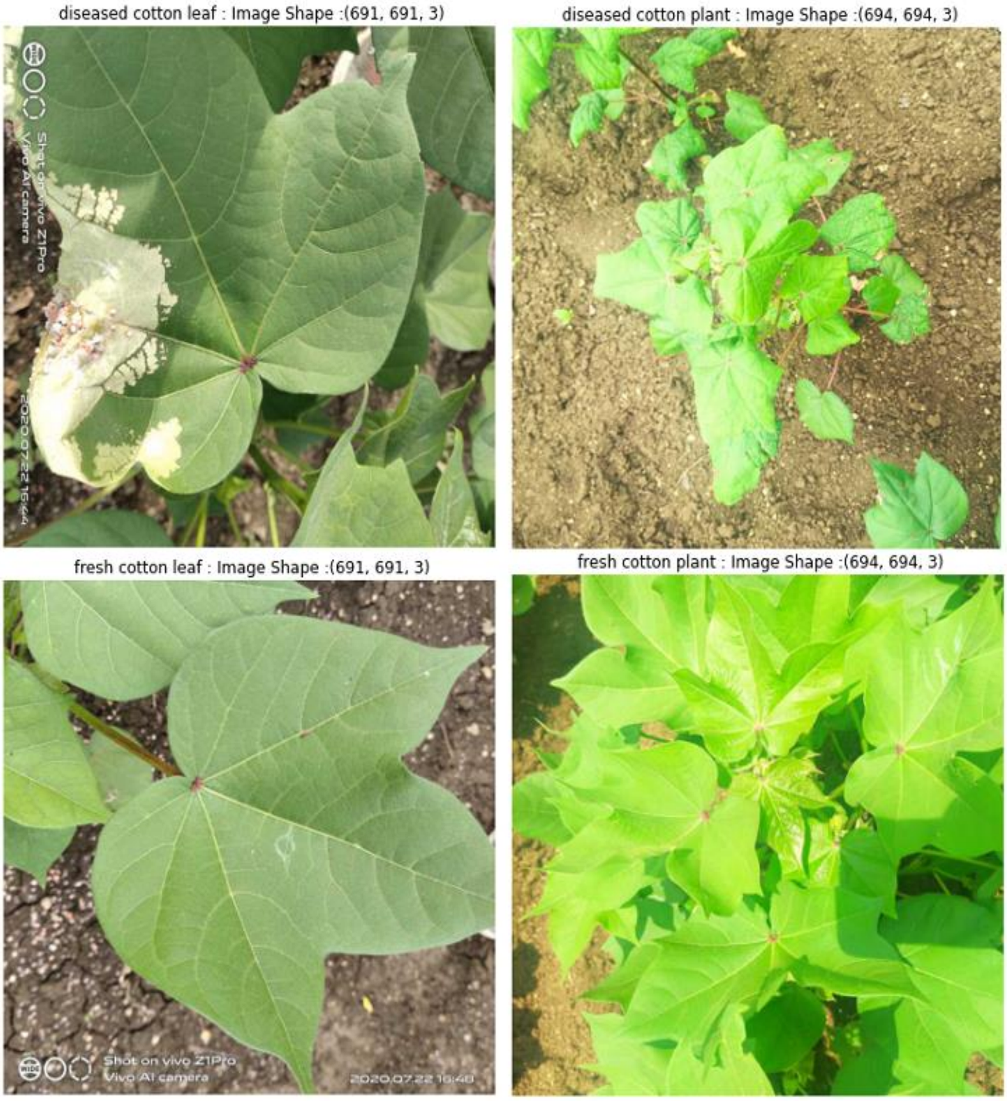


Fig. 3.1 Sample images from the dataset

The dataset of diseased and fresh cotton leaves was downloaded from the cotton disease dataset. After collection of datasets, the images went through pre-processing and after that the images are trained using the model. For different deep learning techniques, data preprocessing includes image filtering and dataset preparation [1]. All the images are resized and data augmentation is done on training set to get a wider variety of images for training purpose. A horizontal shift along with height shift, width shift, zoom range and rotation value of 0.2, 0.2, 0.2 and 0.2 were given in order to perform augmentation.

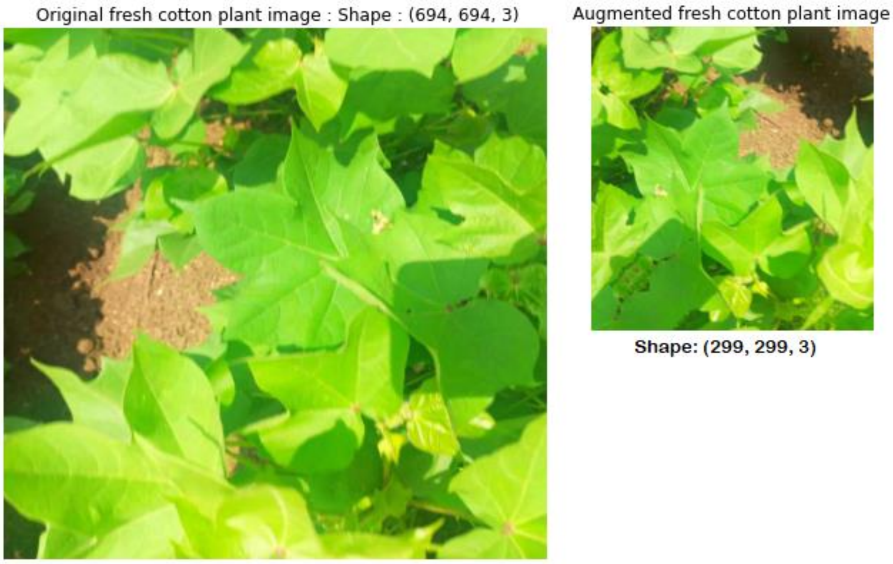


Fig. 3.2 Original Image and Augmented Image

3.2 Fine Tuning

The transfer learning models are trained on large dataset (ImageNet) and therefore used as generalized model for training wide variety of images. These models are improved for a dedicated problem using fine tuning. Generally, it is good practice to take raw samples of a small dataset, with augmentation done on them and get better results from fine tuning. Fine Tuning can be done with one or combination of following techniques:

- A common technique is to shorten final layer which is softmax (generally) and replace it with a new combination of convolutional layers which is called new softmax layer which is in relevance to the specific task. For instance, pre trained model implemented on the ImageNet has 1000 categories in softmax layer and our task is dedicated to classify 20 categories, then newly formed softmax layer could be modified for 20 categories. Back propagation can be then used to fine tune the pre trained weights.

- Using smaller learning rate in order to fit the model. Learning rate is a hyper parameter used to control how quickly a network learns. A big value of learning rate can make a network learn fast but not so optimal weights. Smaller value of learning rate can make a model learn optimally but can take a longer time. So it should not be too large nor too small. The value of learning rate used while developing the pre trained network could be set to lower value in order to optimally train weights for dedicated task.

- Another method to fine tune a network is to freeze the weights of some initial layers of model we wish to use. It is done to use first few layers for capturing general features such as edges and curves which are normally relevant to every problem. By keeping those weights, the focus of network can be shifted to learn dataset specific features in following layers.

In this experiment, a combination of all three fine tuning techniques are used. The base models are used as Inception V3 and EfficientNet B0, along with data augmentation layer. Then, new Softmax layer is added and a learning rate with value 0.001 is given for training the dataset.

3.3 InceptionV3

GoogleNet module was the initialization of Inception CNN architecture. It is good to assist in object detection and image analysis. In ImageNet Recognition Challenge, the Google's Inception convolutional neural network was introduced. InceptionV3 is considered to be third version of the original architecture of version 1. InceptionV3 is very swift and also accurate in performing as CNN classifiers [9]. There have been several developments in breaking out the different versions of Inception model as this is one of major state-of-the-art models that can be used efficiently for image classification. Inception module architecture uses concatenation of feature maps generated by kernels of varying dimensions.

The Inception model architecture (2) is more of a wider approaching architecture rather than deeper. It has total 310 layers. It promotes this type of architecture as accuracy doesn't increase just by increasing the depth of convolutional neural networks. Therefore, different versions of Inception model introduce different components of Filter concatenation and/or layers used.

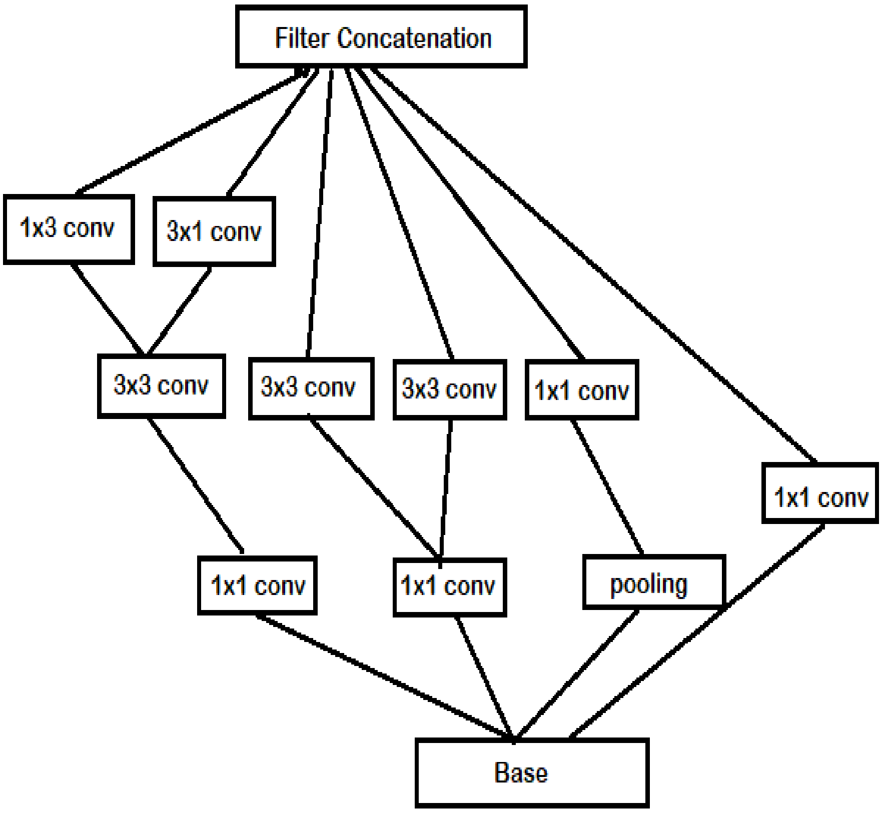


Fig. 3.3 Basic module of Inception V3

3.4 EfficietNet-B0

Mingxing Tan and Quoc V. Le proposed the Efficient model in 2019. The researchers studied model scaling and a deep network can be scaled in three ways: depth, width and resolution. The depth can be increased by adding more layers, width can be increased by adding layers' width-wise and resolution can be scaled by increasing resolution of the input to find fine-grain features of the input. The layer architecture is not changed in scaling and only width, depth and resolution is changed. They found that careful balancing of these scaling dimensions can lead to better performance [8].

A scaling technique was introduced that uniformly scales width, depth and resolution of the network. Compound scaling is done by performing grid search as first step to find relationship between different scaling dimensions that of the baseline network with constraints of fixed resource. Appropriate scaling coefficients are then determined for all dimensions. Then these coefficients are applied to scale up the baseline model to desired target network size.

This method of compound scaling improves model efficiency and accuracy consistently for scaling up pre-trained models like ResNet rather than conventional scaling techniques.

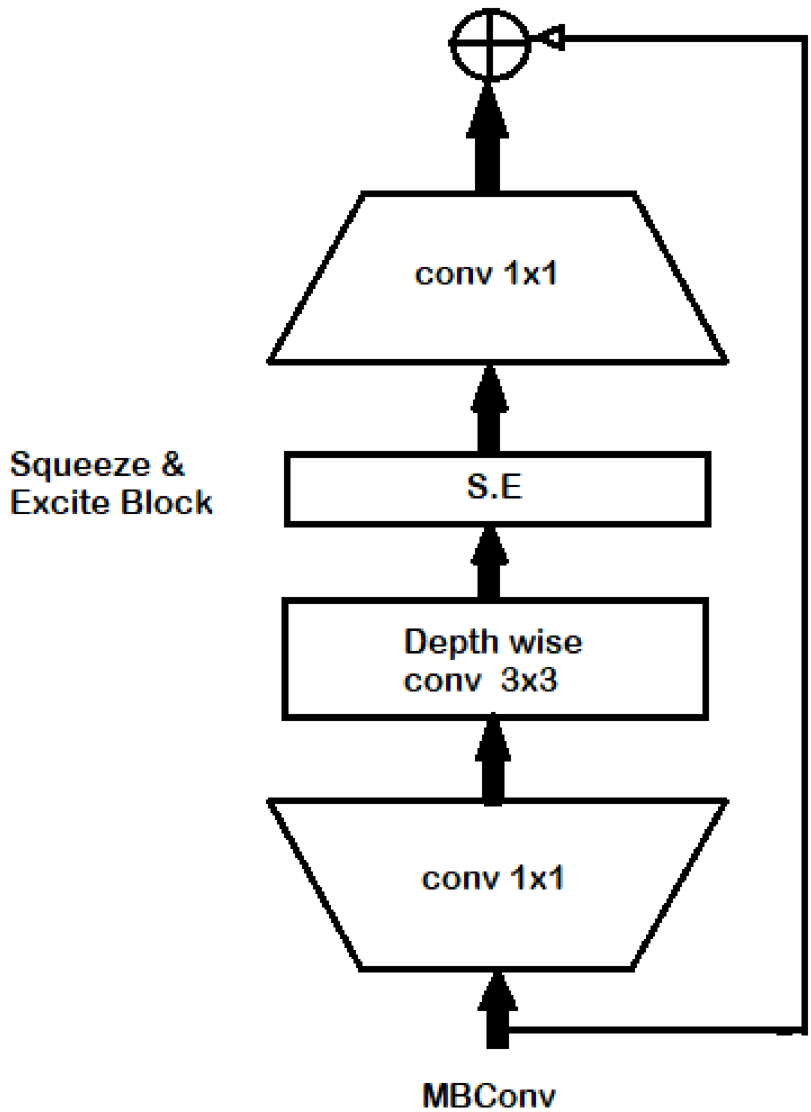


Fig. 3.4 Mobile Inverted Bottleneck (MBConv) Architecture

The authors have proposed to use Neural Architecture Search (NAS) based new baseline network using AutoML MNAS framework. Mobile inverted bottleneck convolution (MBConv) architecture is used [8], as shown in Fig. 3, and scaling is then used to get a group of deep learning convolutional models, called EfficientNets, which are more accurate and efficient in comparison to the earlier CNNs [8].

3.5 ResNet50:

ResNet50 is a ResNet model version that has 48 layers of convolution along with 1 layer of MaxPool and 1 layer of Average Pool.It has 3.8 x 10^9 operations with floating points. It is a ResNet model that is commonly used. Many layers are stacked and conditioned for the assignment at hand in a general deep convolutionary neural network. In residual learning, the aim is to learn some residual functions instead of attempting to learn some characteristics.

Residual can literally be understood as subtraction from the layer's input of the function studied. ResNet uses shortcut connections to do this (directly linking nth layer input to another (n+x)th layer).

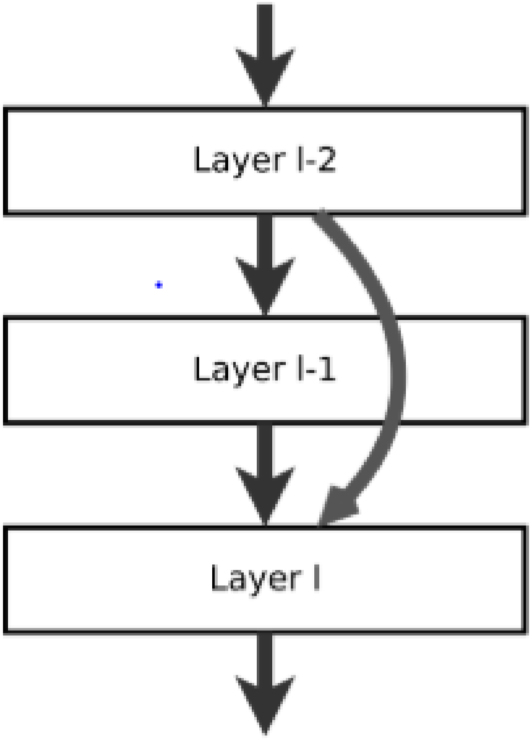


Fig. 3.5 General idea of Residual Network architecture

3.6 VGG16:

VGG stands for Visual Geometry Group. It was proposed by K. Simonyan et. al. This convolutional neural network consists of 16 weighted layers and has been one of the best state-of-the-art networks for the purpose of transfer learning. The architecture of VGG16, shown in fig. 3, consists of 13 Convolutional layers with a 3x3 filter size and 3 dense layers with 4096 neurons in 2 layers and 1000 neurons in final layer.

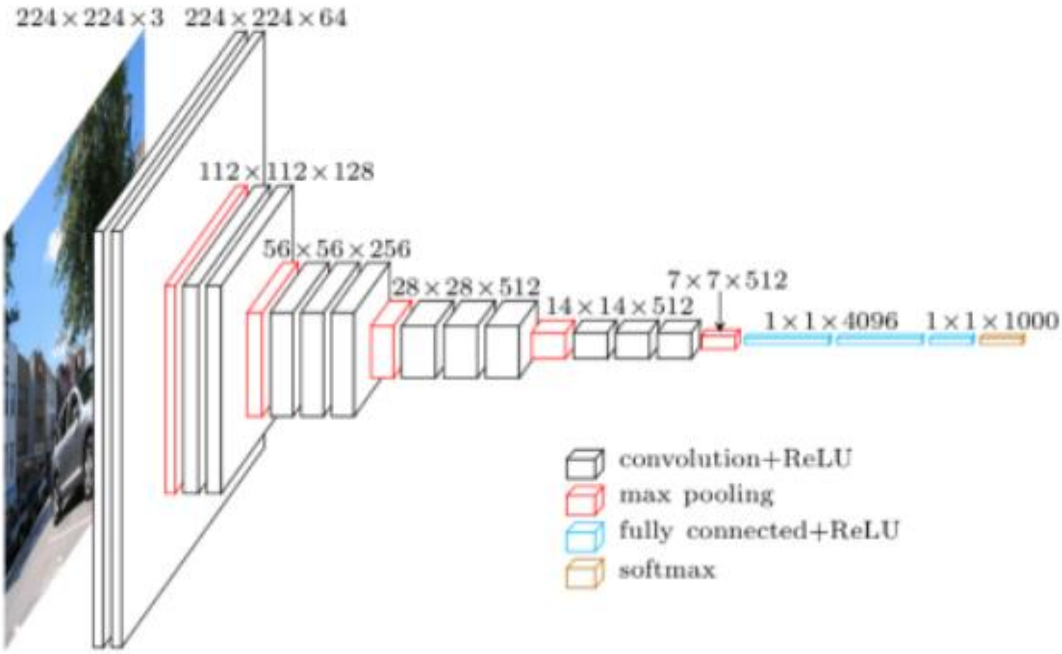


Fig. 3.6 The architecture of model network VGG 16

3.7ResNet152V2:

This residual system of learning is used to promote the preparation of networks that are considerably broader than those traditionally used. The evaluation of ImageNet dataset with 152 deep layers that means 8 times deeper than VGG networks but with lower complexity still.

The5.61 percenttop-4 eror rate is archived topre-rising the network to 152 layers depthing, and this will becomehigher than VGG-16, GoogLeNet (Inception-v1) and ReLU-Net.

ResNet152 function

```
tf.keras.applications.ResNet152(
    include_top=True,
    weights="imagenet",
    input_tensor=None,
    input_shape=None,
    pooling=None,
    classes=1000,
    **kwargs
)
```

Instantiates the ResNet152 architecture.

Fig 3.7 ResNet152 function instantiated using Keras

3.8 Deep-Convolutional Neural Network (Deep-CNN):

The A multilayer deep convolutional neural network has been designed and proposed for more accurate and faster implementation. The detailed architecture of our model is shown in fig. 2. The model consists of 4 convolutional layers with activation function as ‘ReLU’, 5 batch normalization layers, 4 max pooling layers, 5 dropout layers, a flatten layer, a dense layer with ReLU and a final dense layer with softmax activation and size 4 for output categories.

The input image is of size 224 x 224 x 3 and is given to the convolutional layer with 32 filters and kernel size 3. It is followed by a batch normalization layer, a max pooling layer with pooling size (3,3) and a dropout layer with rate 0.25.

These layers are repeated 3 times with change in filter size of convolutional layer to 64 and then, max pooling size of (2,2). After the 4^{th} dropout layer, a flatten layer is added to provide the output from dropout layer to the next layer.

It is followed by dense layer with ReLU activation, batch normalization layer and then 5th dropout layer with rate 0.25. Then final output dense layer is added with softmax activation because of multi-classification problem.

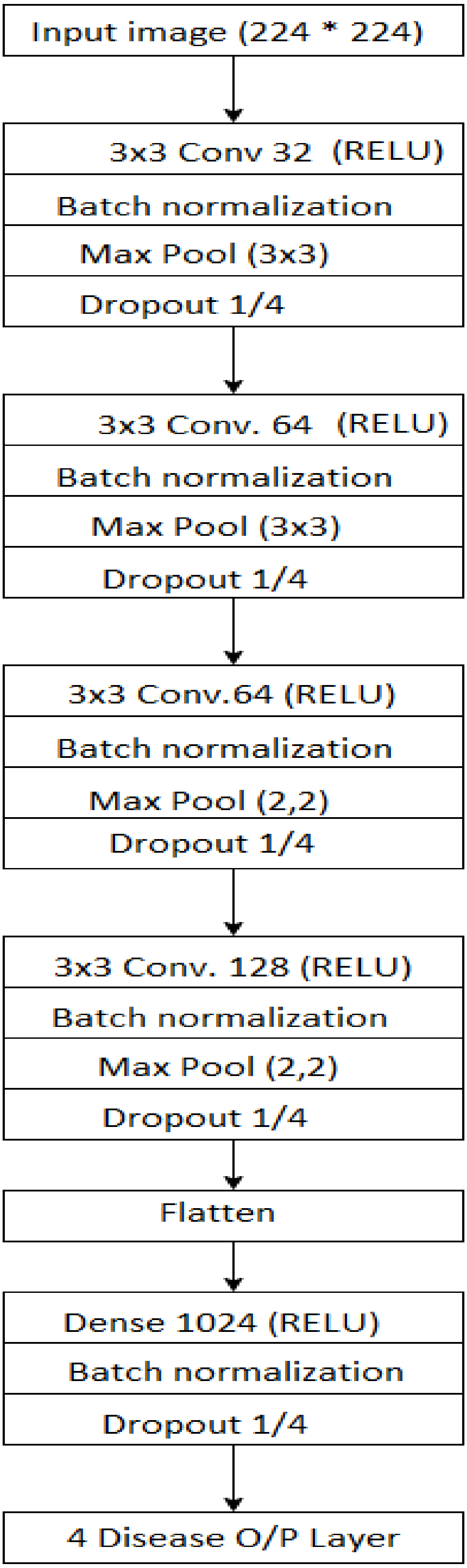


Fig. 3.8 Proposed model architecture

The learning rate for deep-CNN model was determined using an analysis of base model of deep-CNN using loss and epochs using adam optimizer, batch size 32 and 40 epochs. Upon analysis, it was observed that the loss was increasing after the learning rate of 0.001. So, we changed the learning rate to 0.001 for training using the same Adam optimizer, 32 batch size and 30 epochs.

CHAPTER 4

EXPERIMENTS PERFORMED

4.1 Experimental Setup

For Implementation, Windows 10 PC with 64-bit Operating system was used with 8 GB RAM and 1 TB Hard Disk. The model training was done using 12 GB NVIDIA Tesla K80 GPU. The software tools used are Keras 2.2.6, Tensorflow 1.13.0, Matplotlib 3.4.1 and Python 3.8.2. For performing experiments, we used Google Colab and Jupyter Notebooks.

4.2 Dataset Used

For this research, the dataset 1 is collected from Cotton Disease Dataset with 4 classes for Diseased cotton leaves, diseased cotton plant, fresh cotton leaves and fresh cotton plants. Dataset 2 is collected from publically available dataset from internet.

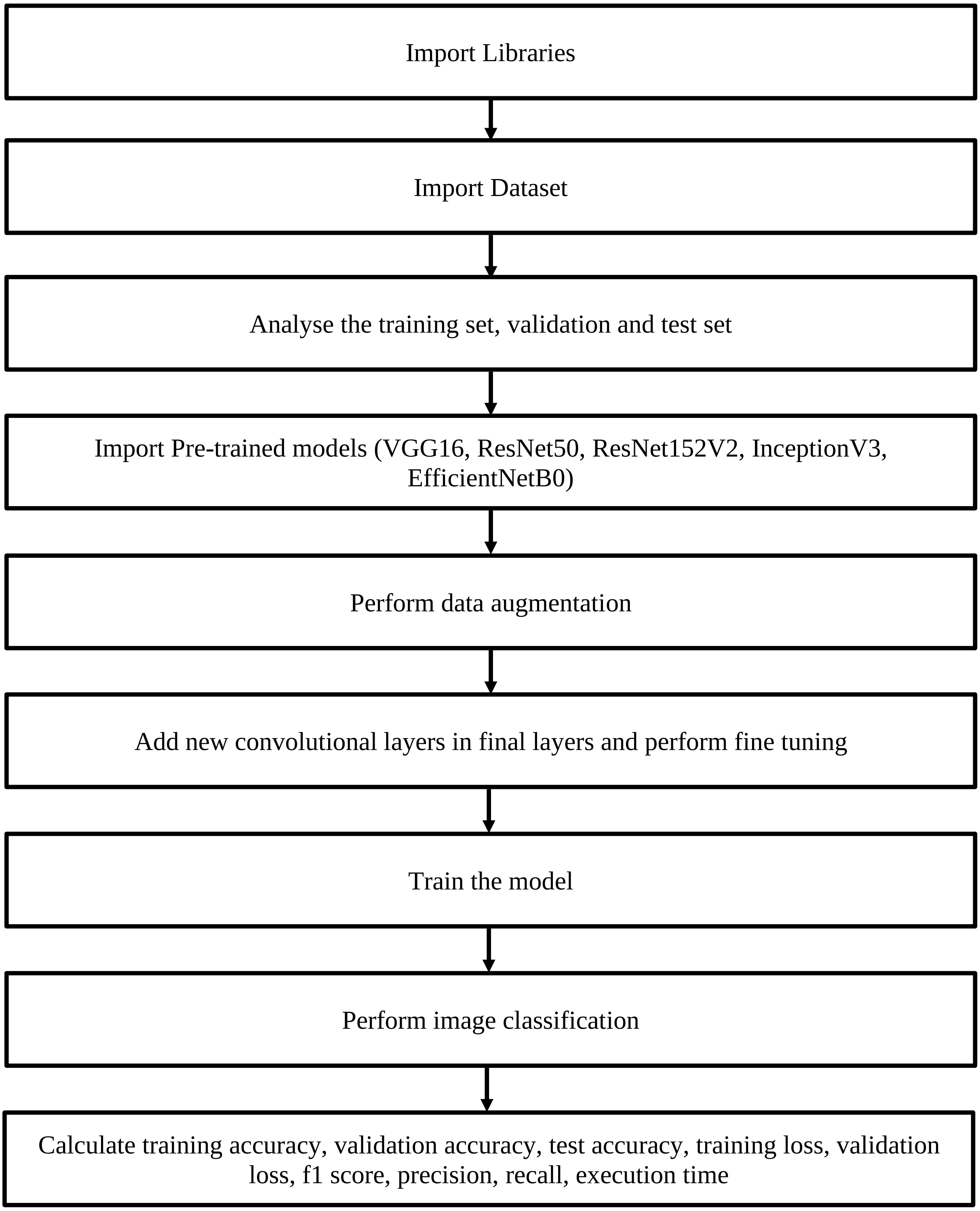
Diseases like white spots, bacterial blight, leaf sucking and chewing pests, grey mildew, Myrothecium leaf spot, Cercospora leaf spot, etc. affect the cotton crops adversely. This dataset has examples of all these different diseases in the diseased cotton plant and diseased cotton leaf categories. Fresh plant and leaves images are present in the cotton fresh plant and cotton fresh leaves categories. Different augmentation techniques like rotation, height shifting, width shifting, zooming the image, and horizontal shifting are applied to the training set using ImageDataGenerator from Keras to generate new images for training.

4.3 Model

The dataset is loaded for training, testing and validation. For every experiment, categorical cross-entropy and accuracy metric are used for evaluation of the models. The performance of both the models before and after fine tuning is shown in Table 1. The metrics used for comparison are accuracy, loss, f1 score, recall and precision.

Another dataset is also fed to the model for testing it for different cotton images taken from internet and resized. Hyper-parameters for the experiments were standardized on all the model networks. Stochastic Gradient Descent (SGD) is used in training for increasing the training speed and easy convergence. Batch size is kept to be 32 to achieve better training stability. For all model networks, the learning rate value was taken as 0.001.

Table 4.1 Steps performed for detection of diseases using transfer learning



Transfer learning hyper-parameters used:

- Batch_size = 32
- Number of epochs = 30
- Image Size = 224
- Learning Rate: 1e-3

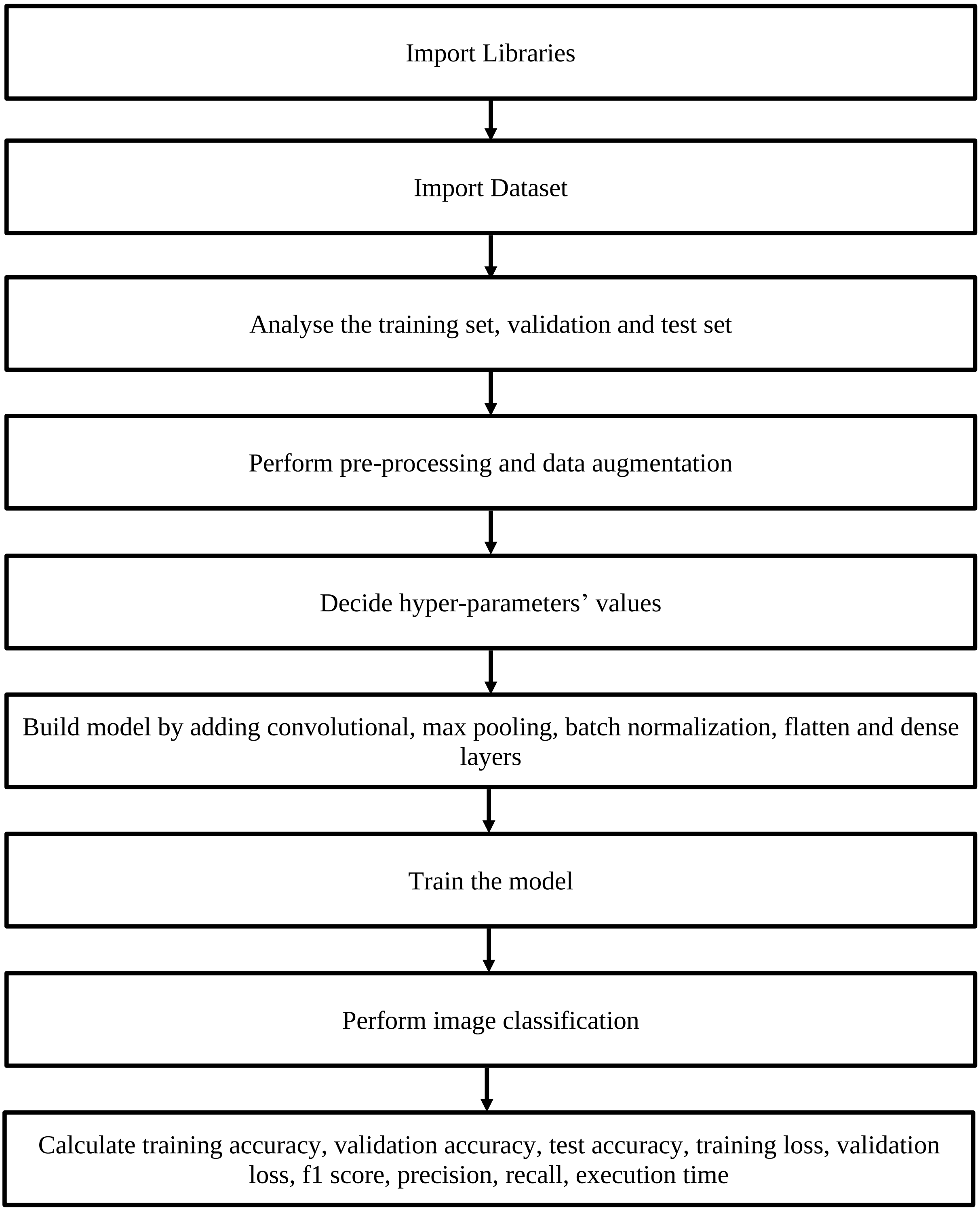
Data augmentation was performed and it was added as a sequential layer of our transfer learning models to use the GPU for image preprocessing with the following values:

- Zoom = 0.2
- Horizontal Flip = True
- Height shift = 0.2
- Width shift = 0.2
- Rotation = 0.2

For performing fine tuning, we added a global average pooling layer, a flatten layer and an output dense layer with softmax activation.

- Number of dense layers = 1
    - Neurons = 4
    - Activation = softmax
- Optimizer = Adam
- Loss = Categorical Cross-entropy
- Metrics = Accuracy

Table 4.2 Steps performed for detection of diseases using proposed method



Deep-CNN hyper-parameters used:

- Batch_size = 32
- Number of epochs = 30
- Image Size = 224
- Learning Rate: 1e-3

To make the comparison with transfer learning comparable, same data augmentation techniques have been applied to this model also.

- Model = Sequential
- Number of Convolution layers = 4
  - Number of filters = 32, 64 or 128
  - Kernel Size = (3,3)
  - Activation = ReLU
- Number of Max-Pooling layers = 4
  - Pooling window = (3x3) or (2,2)
- Number of dense layers = 2
- Number of dropout layers = 5
- Optmizer = Adam
- Loss = Categorical Cross-entropy
- Metrics = Accuracy

4.4 Metrics Used

The parameters required to define the metrices above are true positive (positive entity correctly labelled), true negative (negative entity correctly labelled), false positive (negative entity incorrectly labelled), false negative (positive entity incorrectly labelled).

Of the metrices mentioned, the accuracy is the number of correct predictions upon the all the predictions whether correct or incorrect. It is given by the first (1) equation; signifying t as true, f as false, p as positive and n as negative.

$$\boldsymbol{accuracy} = (\boldsymbol{tp}+\boldsymbol{tn}) \,/\, (\boldsymbol{tp}+\boldsymbol{tn}+\boldsymbol{fp}+\boldsymbol{fn}) \tag{1}$$

To understand how much of true positive values were correct from all the predicted positive values we make use of precision. It is given by (2) and shows the ability of the model's classifier to not incorrectly label a sample as positive if it is not positive.

$$\boldsymbol{precision} = \boldsymbol{tp} \,/\, (\boldsymbol{tp}+\boldsymbol{fp}) \tag{2}$$

Recall is used to know the actual number of true positives which were recognized correct asnd is given by equation (3).

$$\boldsymbol{recall} = \boldsymbol{tp} \,/\, (\boldsymbol{tp}+\boldsymbol{fn}) \tag{3}$$

F1-score which is calculated using precision and recall, as it is the weighted average of the two. It could be used if we need to strike balance among Precision and Recall or if the class distribution is uneven.

$$\boldsymbol{f1} = \boldsymbol{2} * \boldsymbol{precision} * \boldsymbol{recall} \,/\, (\boldsymbol{precision}+\boldsymbol{recall}) \tag{4}$$

CHAPTER 5

RESULTS

The performance of all the models with respect to accuracy vs epochs graph and loss vs pochs graph is analyzed in this work. In the first part of the research, comparison of before and after fine tuning using pre-trained models like Inception V3 and EfficientNet B0 was done. The graphs of the above said comparison is shown in fig. 5.1 and 5.2.

From these, we can see that after fine tuning, the accuracy is increasing and loss is decreasing.

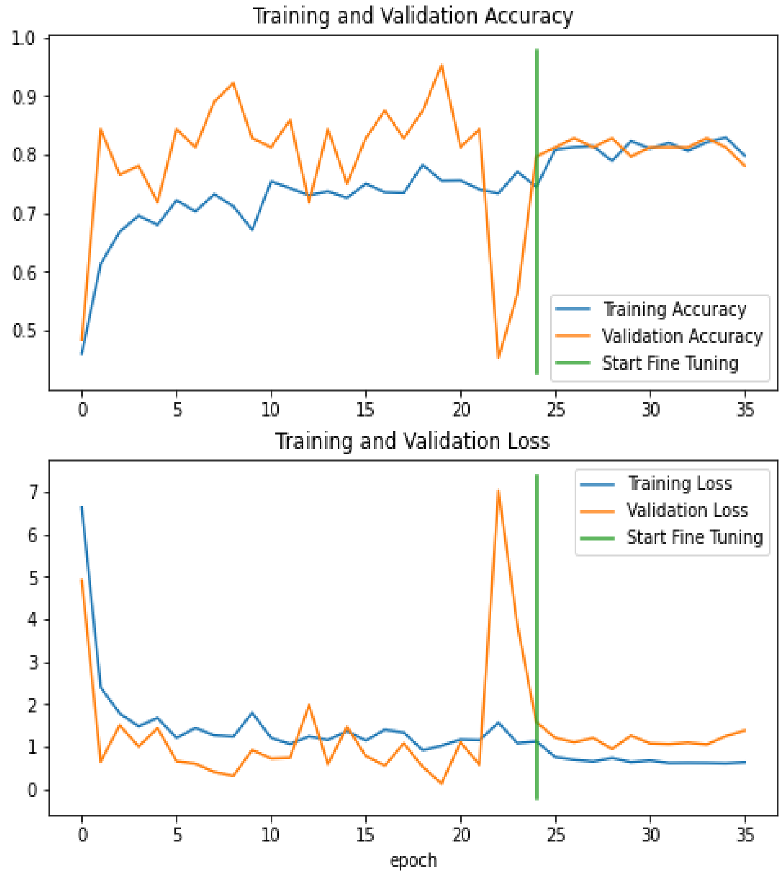


Fig. 5.1 Accuracy and Loss graphs of InceptionV3

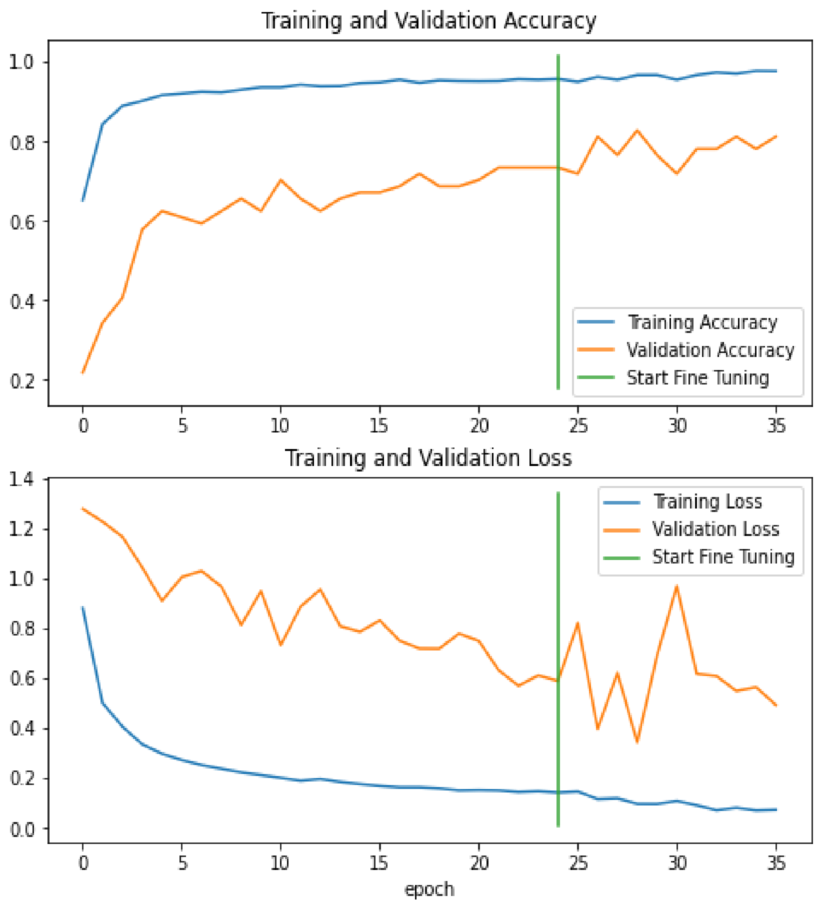


Fig. 5.2 Accuracy and Loss graphs of EfficientNetB0

Further, in the second part of the research, we took a comparison of the different techniques that can be used in transfer learning and popular state-of-the art models like VGG16, ResNet50 and ResNet152V2. The same techniques were implemented on these models as were implemented in the first part of the project. The graphs of accuracy and loss with respect to epochs for VGG16, ResNet50 and ResNet 152V2 are depicted in the fig. 5.3, 5.4 and 5.5.

From these graphs, it is concluded that transfer learning are good techniques for detecting diseases in plants but they are time consuming in operation and have very large number of parameters. Therefore, a model is proposed which is implemented from scratch by adding convolutional layers in the sequential model. The architecture is inspired by the VGGNet architecture.

The performance of the proposed model can be seen in fig. 5.6. The fig. 5.6 depicts that the training and validation accuracy of the proposed model is increasing as the number of epochs is increasing. This indicates that our model is neither over-fitting nor under-fitting. Also, the training and validation accuracies achieved are comparable to the pre-trained models' accuracies. Not only that, the execution time for implementing the deep-CNN model is lesser by 50% in comparison to the other transfer learning methods used.

The different metrics for comparison of performance of proposed model with the pre-trained models can be seen in Table 5.1 and 5.2.

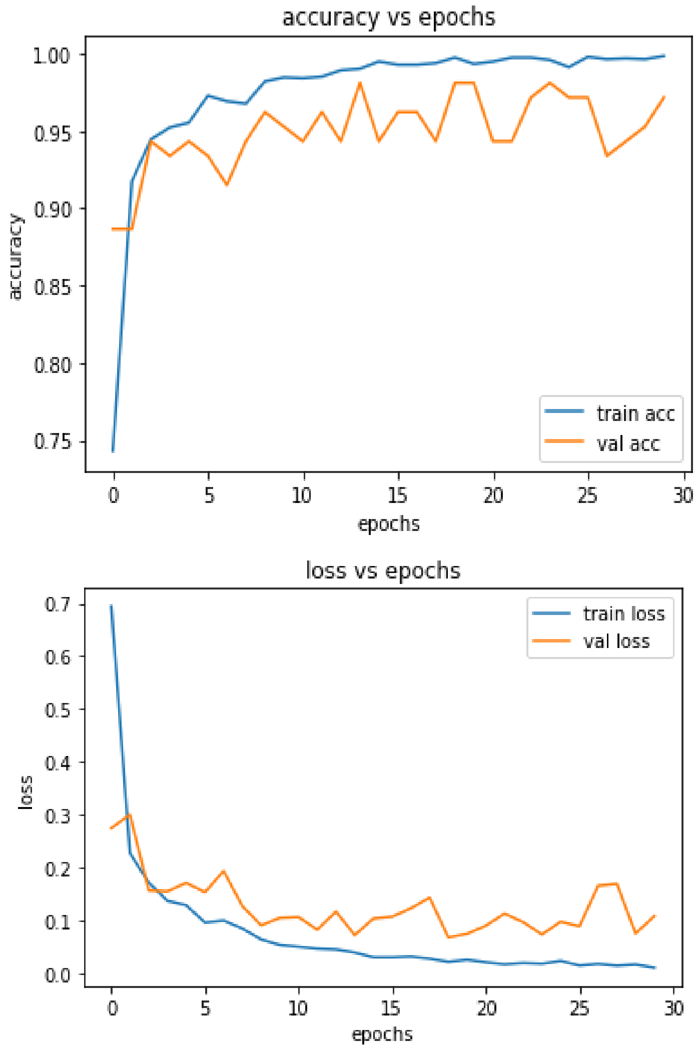
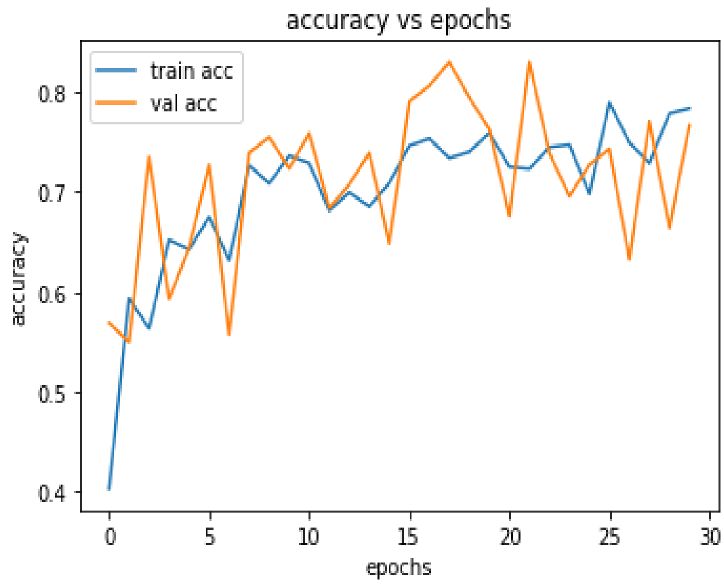


Fig. 5.1 Accuracy and loss analysis of VGG16



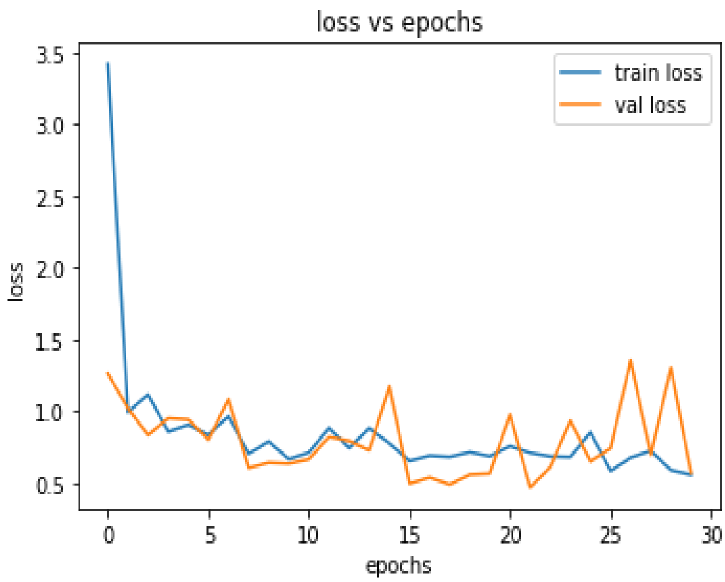


Fig. 5.4 Accuracy and loss analysis of ResNet50

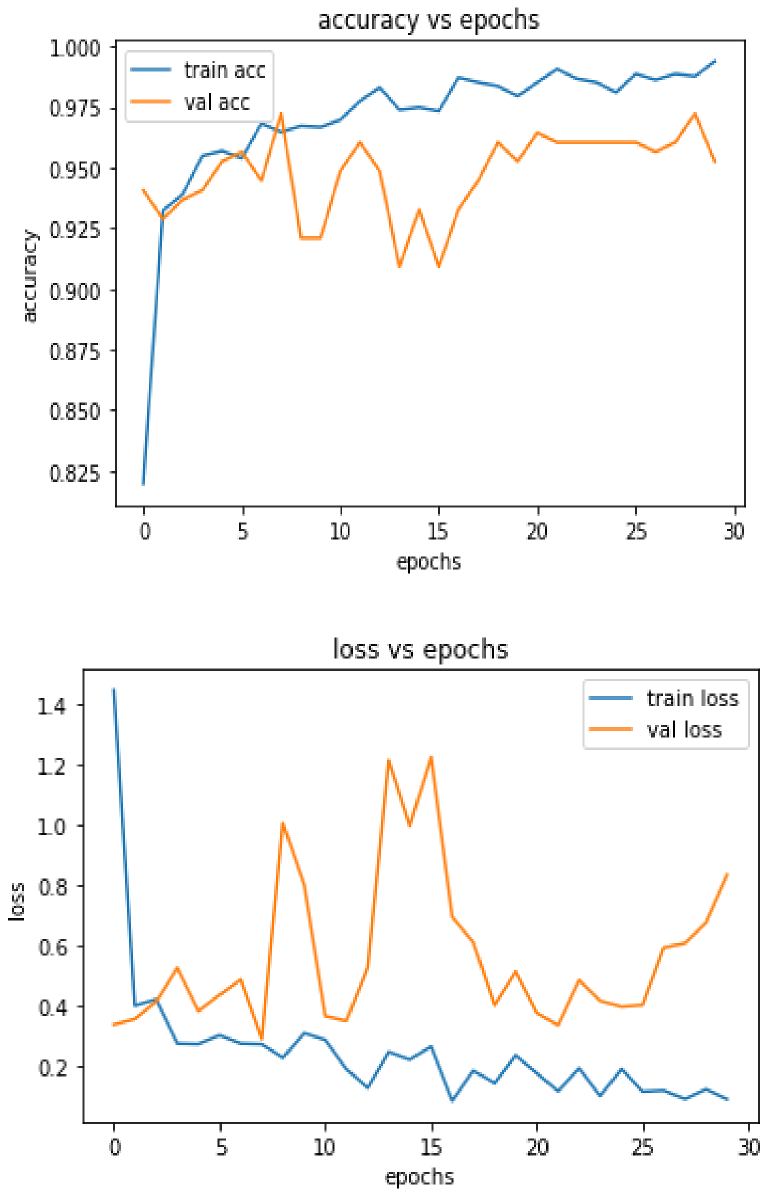


Fig. 5.5 Accuracy and loss analysis of ResNet152V2

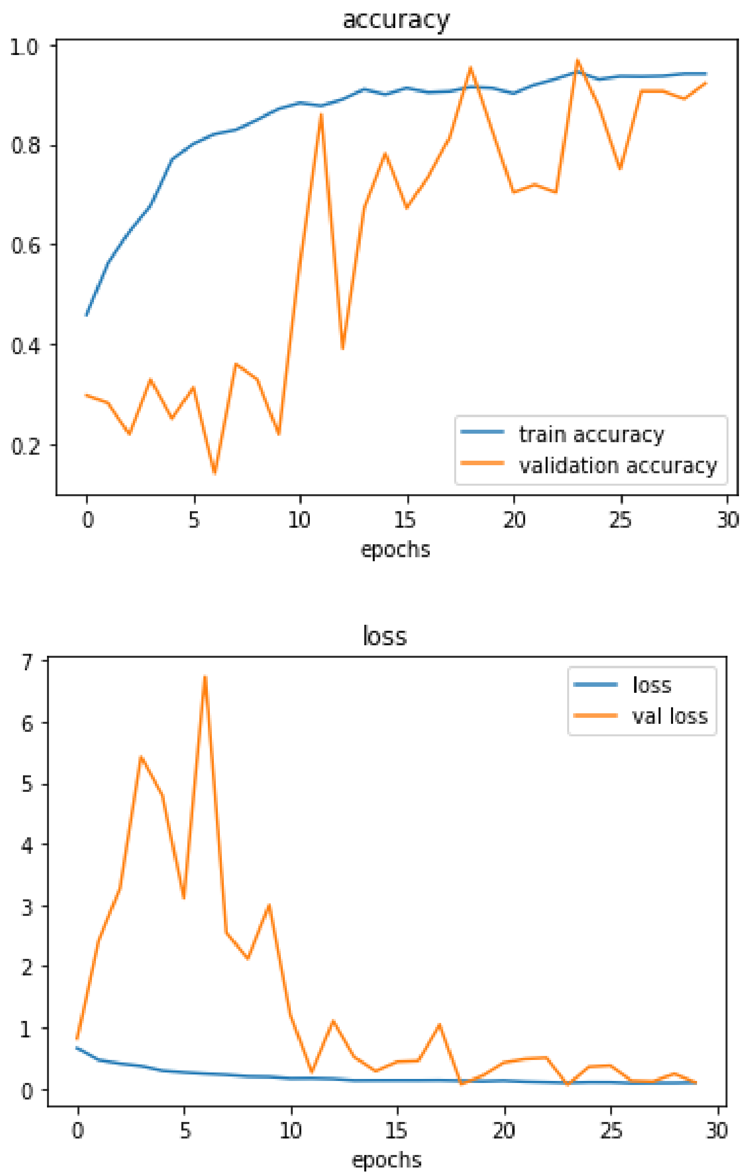


Fig. 5.6 Accuracy and loss analysis of proposed model

During this research, the effect of fine tuning on pre trained convolutional networks was observed using cotton plant disease detection. The focus was using data augmentation and fine tuning to enhance the performance of pre-trained models. Data augmentation is used because the size of training set is less and it prevents overfitting. Therefore, the model tends to overfit on a small dataset because a large variety of data is not being provided for training. With data augmentation, the model training is done effectively as we are changing the width, height, and applying rotation, zoom and horizontal shift.

Table 5.1 Performance of all the models with different epochs

Model specs		**10 epochs**		**30 epochs**			
Model	Params	Training Acc.	Validation Acc.	Training Acc.	Validation Acc.	Test Acc.	Time (in sec)
VGG	138.35M	95.54%	94.34%	99.33%	97.17%	96.04%	2515
ResNet50	25.63M	64.22%	64.43%	72.53%	83.00%	71.70%	2402
ResNet 152V2	60.38M	95.69%	95.26%	99.08%	96.05%	98.01%	2748
Inception V3	23.85M	66.83%	76.56%	82.93%	78.12%	70.36%	2515
Efficient NetB0	5.3M	90.47%	56.25%	97.69%	88.93%	89.62%	1759
Proposed	**4.8M**	**65.09%**	**43.75%**	**94.52%**	**96.88%**	**98.11 %**	**1079**

Table 5.2 depict the results according to different metrics. In terms of overall performance considering all the metrics for comparison, our model is performing better than the pre-trained models using transfer learning.

Table 5.2 Performance of the models on different metrics

Metrics	**VGG16**	**ResNet50**	**ResNet 152V2**	**InceptionV3 fine tuned**	**EfficientNetB0 fine tuned**	**Proposed model**
Precision	0.91	0.79	0.89	0.76	0.91	0.92
F1 score	0.91	0.76	0.89	0.66	0.90	0.90
Recall	0.90	0.76	0.89	0.66	0.90	0.90

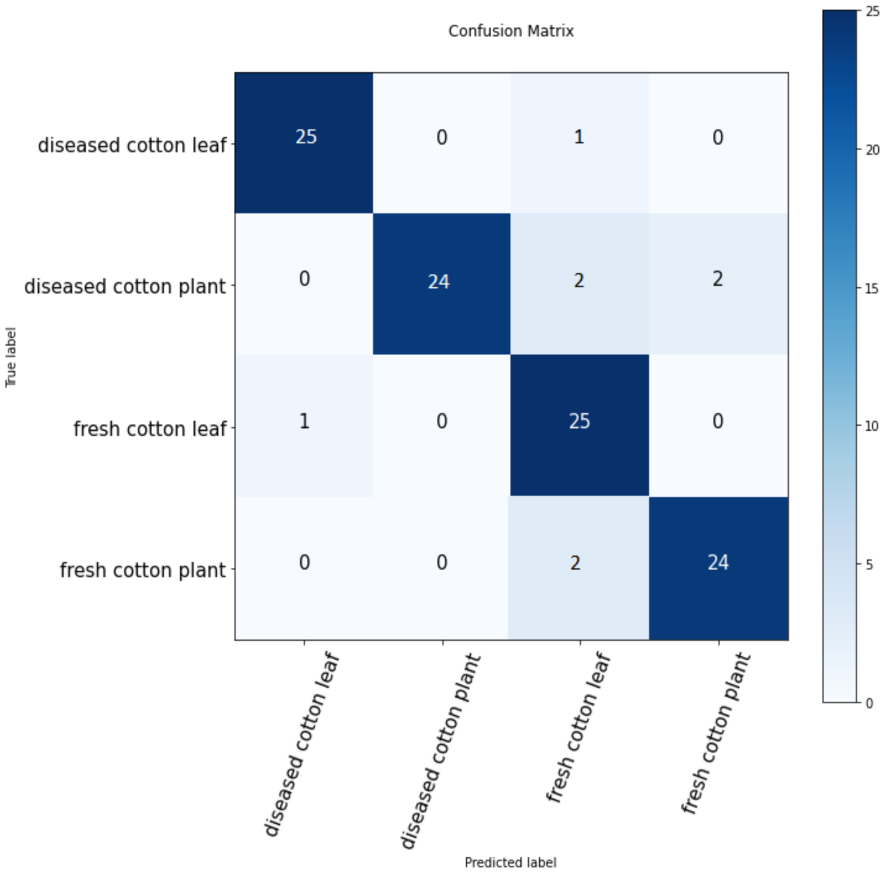


Fig. 5.7 Confusion matrix using proposed model

The confusion matrix is also drawn for analysis of accuracy of our model in fig. 5.7. The correct detections for all classes were 98 and incorrect were 8.

CHAPTER 6

CONCLUSION & FUTURE SCOPE

Cotton plants production is vital for our country's economy and therefore preventing the diseases in cotton plants can help manyfold in the production of cotton-based products. Therefore, automated detection of diseases can help farmers in producing highly efficient crops. Transfer learning has been gaining popularity for detection of diseases, but this technique is susceptible to over-fitting. Therefore, we have done a comparison of transfer learning using pre-trained models with our own proposed sequential deep-CNN model. We have detected diseases like Aphids which are leaf sucking pests and white spots on leaves due to excessive spray of herbicides and pesticides which can cause poor production and even death of plants. Experimental results depicted that the proposed model performed well on unseen data and gave better results than transfer learning techniques along with faster detection. Further, we are planning to implement the proposed detection model on different types of diseases other than described in this work.

Since the technique is very novel, many improvements lie for it in the coming future. With the improvements in technique, increase in accuracy and lower time can also be expected for our problem statement. Further, more datasets of different types of plants and diseases can be introduced for the proposed work to make the applications wider.

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LIST OF PUBLICATIONS

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November 01 to 02, 2021

CERTIFICATE OF PRESENTATION

This certificate is awarded to
Himani Bhatheja from Delhi Technological University, India
for presenting the paper titled
"Transfer Learning And Fine Tuning Based Early Detection Of Cotton Plant Disease "
having authors
Himani Bhatheja and N. Jayanthi
*at the conference "**MISS-2021**"*
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Himani Bhatheja and N. Jayanthi

From

Delhi Technological University, India

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Techno College of Engineering Agartala, India.

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