Tomato Leaf Disease Detection using Resnet-50 and MobileNet Architecture

by

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Approval

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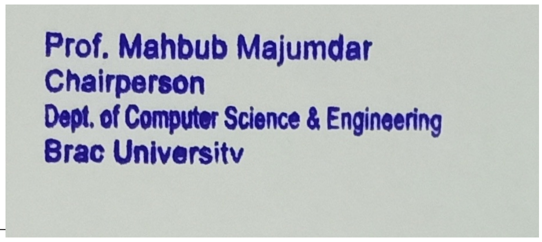

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Abstract

Diseases in Tomato mostly on the leaves affect the reduction of both the standard and quantity of agricultural products. Several diseases such as bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites, two-spotted spider mite, yellow leaf curl Virus, mosaic virus common diseases found in tomato, thus, real-time and precise recognition technology is essential. To detect plant leaf diseases, image processing techniques such as image acquisition, segmentation through two technical models Resent50 and MobileNet are implemented. These two methods are implemented by the transfer learning method which widely used for deep learning, where every step is get improved than the previous one. The deeper stages the execution goes, the more accurate result tends to yield. In Resnet-50 Model, experimental results fluctuate from 94 percent to 99.81% and In MobileNet the predictions correction resonates within 95.23% to a maximum of 99.88% which buttress the prediction with respect to the actual data by analyzing accuracy and execution time to identify leaf diseases.

Keywords: Transfer learning; MobileNet architecture; Resnet-50 architecture; Deep learning; fine tuning; segmentation

Dedication

This Research is dedicated to my beloved parents who have been my source of inspiration.

Acknowledgement

All praises are due to The Almighty Allah, The Most Gracious, The Most Merciful who blessed us to be able to pursue an undergraduate degree at BRAC University. Our deepest gratitude goes to our Supervisor, Mr. Hossain Arif and our CoSupervisor, Md. Saiful Islam for supporting us, guiding us and helping us every step of the way to complete this thesis.

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation and Goals

Though the world is advancing towards technologies day by day, still our ancient methodologies are in use. If any plan is affected by insecticides or diseases, we are finding existing methodologies to resolve which kill our time, work and financial cost. But, as agriculture plays a key role in the development of humankind, it is rather disappointing of keeping away this sector in backward ideologies. Therefore judicious management of all input resources such as soil, seed, water, fertilizers, etc. is essential for sustainability. The naked eye observation of farmers followed by chemical tests is the main way of detection and classification of agricultural plant diseases.

In developing countries, farming land can be much larger and farmers cannot observe each and every plant, every day. Farmers are unconscious of non-native diseases. Discourse with experts for this might be time-consuming as well as costly. Also, unnecessary use of pesticides might be harmful and noxious for natural resources such as water, soil, air, food chain, etc. as well as it is expected that there need to be less poisoning of food commodity with pesticides.

As diseases are inevitable, detecting them plays a major role, especially inaccurate way by using modern technological knowledge. Otherwise, identification of plant disease wrongly will lead to a huge loss of time, hard cash, labor, yield and product quality and value. Manual recognition of disease though works well, the prediction may result in the wrong direction in case of changing environmental or milieu conditions.

By utilizing technology development we can use image processing for the detection of Tomato plant disease by analyzing its deficiency. We can analyze the indicators of disease on leaves, stems, flowers, etc. In general, a plant needs mineral nutrients such as Nitrogen, Phosphorus, Potassium, Sulfur, Magnesium, Manganese, Molybdenum, Zinc, Boron, Calcium, Copper and Iron and so on.

When the plants fall into the pray of insecticides or diseases, its danger sign is showed usually on the leaf. With the help of the color of the leaf, it is easier to detect the deficiency of tomato. So here we use the leaf as a sample for the identification of disease affected tomato.

1.2 Components of detection

The diagnostic system would include the following Transfer learning Model for data processing:

- Resnet-50 Architecture

- MobileNet Architecture

1.3 Scopes and Obstructions in Experiment

Restraints in identifying nutrient deficiency symptoms include the following:

- We are predicting our result by collecting samples from online.

- All types of diseases are not included in our experiment.

- The only Leaf attacked diseases are under experiment.

- Diseases without leaf symptoms cannot be traceable through these methodologies.

- Some of the symptoms look similar in different cases.

- More than one diseases can be attacked.

1.4 Overview

We experiment with the detection of tomato diseases of different kinds by taking specimens from online. Here, Transfer learning methods have been implemented which assure the deep learning process effectively. The two transfer learning methods, named Resnet-50 and MobileNet are implemented over different diseases for several different input options. Executing more and more stages the result outreaches to accurate results with close to cents. These training models help in detecting the diseases for tomato for present snippets which methods can be further elongated.

We have taken help from other resources for help in this field albeit these resources support our methodology to gain a more accurate result. Though our data sets are not collected directly by us, but online, there may remain some fluctuations. But by the deep learning process, the flaws become overcome.

Chapter 2

Literature Review

Our thesis is about tomato disease detection through Resnet-50 Architecture and MobileNet Architecture which are Transfer learning Models . This transfer learning is used more efficiently in second time use by deep learning method giving training. Transfer learning model is a vast field of application for modern technology. Many research has been done in this field , even in agricultural field to find the solution accurately. These researches were very helpful in our finding and influence on our modeling of detection tomato diseases.

Related articles

[1] In 'High-Performance Deep Neural Network-Based Tomato Plant Diseases and Pests Diagnosis System With Refinement Filter Bank' author proposed a structure based on deep neural networks that performs object-specific bounding boxes for efficient real time identification of malady and pests of tomato plants. The method implemented a Refinement Filter Bank framework for Tomato Plant Diseases and Pests identification where the CNN filter Bank gives decision whether or not a target belongs to category. The result obtained a recognition rate of approximately 96% which developed from the existing work result of 13% in tomato diseases and pest recognition.

[2] In 'Tomato crop disease classification using pre-trained deep learning algorithm' author used pretrained deep learning architecture named AlexNet and VGG16 net. The evaluation has been done by modifying the number of images, setting various mini batch sizes and varying the weight and bias learning rate using 13262 image samples. The result comes by using VGG16 net and AlexNet are 97.29% and 97.49% respectively.The best accuracy achieved using 373 sample images but the result accuracy plummeted by fine-tuning weight and bias learning rate for till 30 image rates, then waxed. In VGG16 net case the accuracy dropped with the growth of learning rate.

[3] In ‘Tomato Leaf Disease Detection Using Convolutional Neural Networks’ author adopts a slight variation of the convolutional neural network model called LeNet to detect and identify diseases in tomato leaves where achieved an average accuracy of 94-95 % indicating the feasibility of the neural network approach even under unfavorable conditions.

[4] In ‘Computer Vision Based Detection And Classification of Tomato Leaf Diseases’ author compared the performance of K-nearest neighbor (KNN) and multi class Support Vector machine (SVM) and proposed a neural network based classification of potato leaf disease which uses the GLCM method to extract the color and texture features. The method performs in 92% accuracy. This method also associated with identifying lemon leaf diseases by Gradient boosting technique.

[5] In ‘Image Based Tomato Leaves Diseases Detection Using Deep Learning’ author trained a deep convolutional neural network to identify 5 diseases from the data-set of 9000 images of tomato in infected and healthy conditions of Tomato leaves. Author used smartphone-assisted plant disease diagnosing process on the burgeoning image data sets. The neural network feasibility of this approach achieved an accuracy of 99.84% for these selected diseases.

[6] In ’Tomato crop disease classification using pre-trained deep learning algorithm’ author performed AlexNet and VGG16 net by pretrained deep learning architecture. And the accuracy from the 13262 sample images were 97.29% and 97.49% respectively.When the sample number reaches to 373 it gives the most accuracy.Here, AlexNet provides a good accuracy than VGG16 respect to the minimum execution time interval.

[7] In ’Real Time Grape Leaf Diseases Detection’ author find diseases in plant which proves to be effective and convenient for production losses occur for diseases on the plant.Author detects, identifies, and accurately quantifies the first symptoms of disease that are created by bacteria, fungi, virus etc using image acquisition, image pre-processing, features extraction and classification of neural network. The result came out with accuracy of 92.94%.

[8] In ’Tomato leaves diseases detection approach based on support vector machines’ authors proposed SVM-based tomato diseases noting procedure. 200 data sets are recognised from two different types tomato disease of 249 numbers by this methodology.Here, SVM is employed using three different kernel functions which are Cauchy, Invmult and Laplacian Kernel. Among them cauchy and Laplacian kernel functions reaches accuracy to 100% and Invmult kernel to 78%.

[9] In ’Automatic detection of yellow rust-in wheat using reflections measurements and neural networks’ authors proposed a simple and cost-effective optical device for remote disease detection, based on canopy reflections in several wavebands. Here,

the difference in spectral reflections between healthy and affected wheat plants were probed at an early stage in the improvement of the ”yellow rust” disease.Detection algorithms were developed by deep neural networks and multi-layer perceptions.By 5137 leaf spectra results performance shoot up from 95% to more than 99%.

[10] In ’Plant Disease Diagnosis System for Improved Crop Yield’ author proposed work of an efficient diagnosis system by processing acquired digital processed images of leaves of the crop. These images are sent through a set of pretrained methods for image enhancement.The advisory helps in farming community in efficacious plan making to save their plants from insecticides and increase its yielding.

[11] In ’Detection of Palm Oil Leaf Disease with Image Processing and Neural Network Classification on Mobile Device’ authors propose application of image processing and machine learning in recognizing palm oil diseases based on visual appearances. The method with linear complexity process to come down processing time so that it can be gadget-ed in ambulant device. Through image processing,it was learned using Neural Network method in machine learning way and resulted to 87.75% standard precision.Below figure is illustrated in the experiment and Figure-2.7 shown the authors experimented result in processed image pixel.

Chapter 3

Methodology

3.1 Models

We used two Transfer learning Models named Resnet-50 Architecture and MobileNet. These model's architecture and modus operandies are demonstrated below.

3.1.1 Resnet-50 Architecture

We applied in this model hyperparameter tuning method to observe the different kinds of losses such as low valid loss, low error loss, training loss and in consequences applied the same rule several times until best results and accuracy are found.

3.1.2 MobileNet Architecture

Here we applied adam(default) for optimizer found until the best model with high accuracy from callbacks condition=(lr_reducer, early_stopper, csv_logger, model_checkpoint) running condition of epochs was 100 with validation data from Github Repository.

3.2 Transfer Learning

When we try to teach a child identifying fruits, we approach by showing apples of different colors like red apples, green apples, pale yellow apple, etc. and show scattered types of apples like lemon, apples, mangoes, etc. By showing in different settings, the child develops itself to choose the right one.

The main objective of Inductive transfer learning is to improve the performance of the target predictive function. Inductive transfer learning needs a few data in the domain as the training data to predictive function. When source and domains both contain the labeled data, then we execute multitasking transfer learning and in different configuration self-learning transfer learning.

Similarly in the case of transductive Transfer learning Domain is Different but Task Transfer Learning is in state of similarity. Unsupervised transfer learning is similar

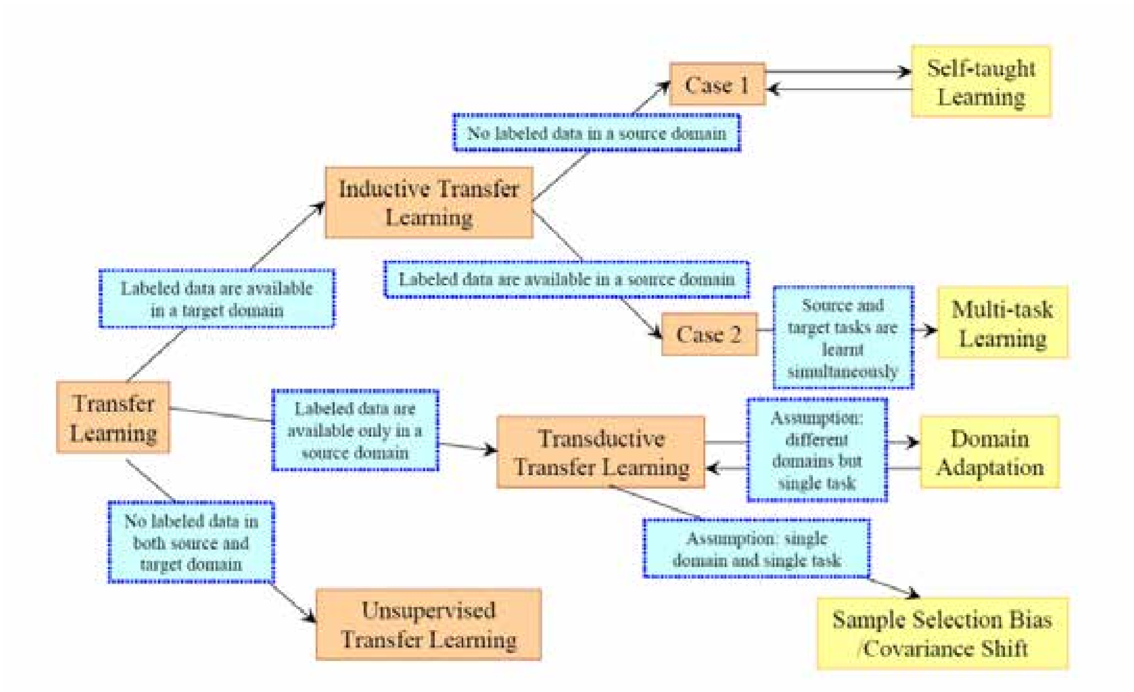

Figure 3.1: Transfer Learning Method flow

to inductive transfer learning where the target task is different from but related to the source task. Here the domain of the source and target task is selfsame.

3.2.1 Transfer Learning strategies to Deep Learning

Training data and time are needed to Deep Learning for computer vision or sequential text processing or audio processing. It saves the future use by a trained model. These pre-trained models widely used for Transfer Learning referred to as Deep Transfer Learning.

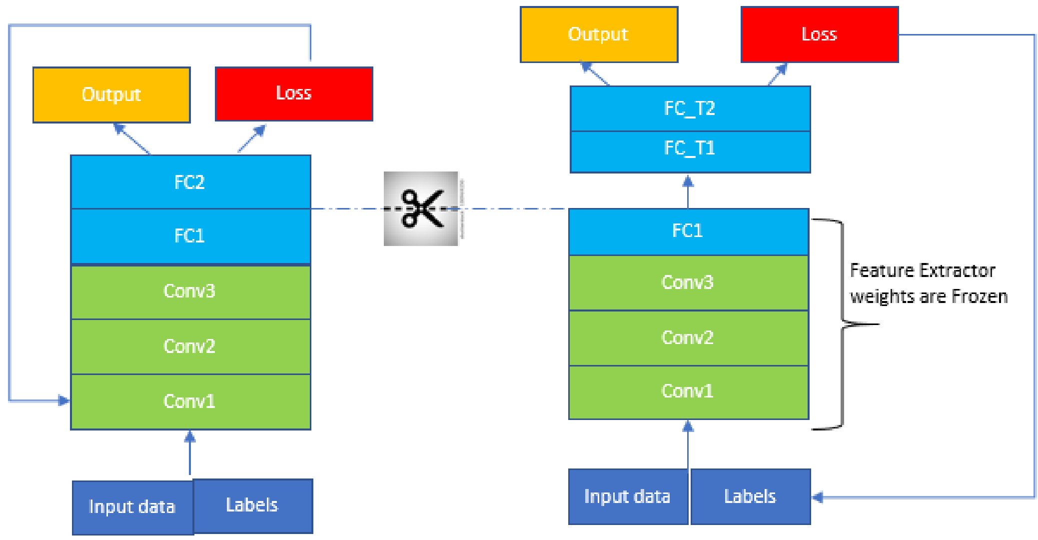

Figure 3.2: Implementation of Transfer Learning Method

The strategies for Deep Transfer Learning are the pre-trained model as feature extractors and Fine-tune the pre-trained models.

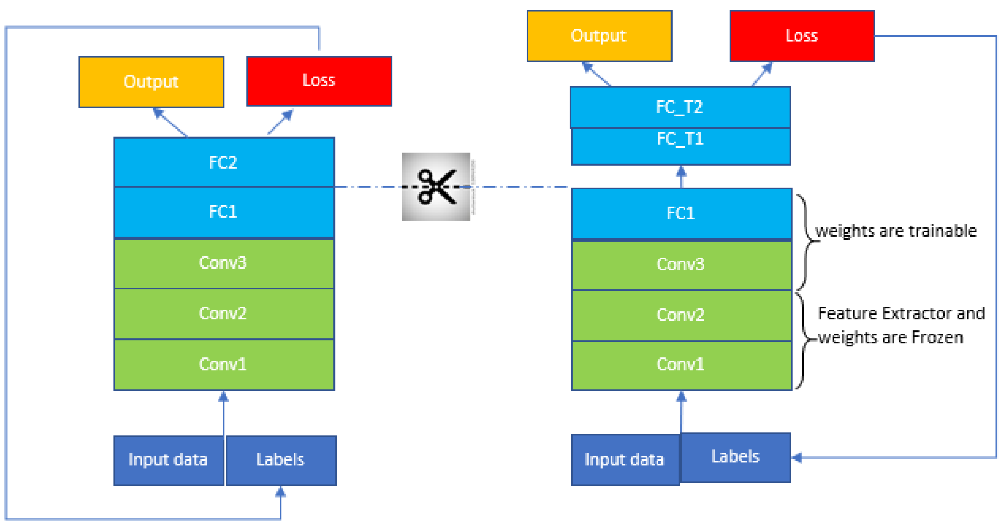

Figure 3.3: Implementation of Transfer Learning Method

Pre-trained deep neural networks for Computer Visions are Resnet-50, VGG-19, VGG-16, Inception V3, MobilNet, Xception and so on. To implement Transfer learning, removing the last predicting layer of the pre-trained model and replacing them with predicting layers. FC-T1 and FC-T2. Weights of these pre-trained models are used as a feature extractor and refurbished during the training.

3.3.1 Designing the Resnet-50 network

Plain VGG and VGG with Residual Blocks using 3*3 filters mostly sampling with CNN layers with stride 2. It is a 1000-way fully-connected layer in the end.

ResNet, short for Residual Networks is a neural network used as a strength for many computer vision tasks. The fundamental breakthrough with ResNet-50 was to train extremely deep neural networks with 150+ deeper layers. Deep networks are tough to train for the vanishing gradient problem — as the gradient is back-propagated to previous layers, repetition can make it smaller. So the network goes deeper, its production gets to come down fast.

ResNet-50 first institutes the skip connection. which can be written as two lines of code:

X_shortcut = X Store the initial value of X in a variable
Perform convolution + batch norm operations on X
X = Add()([X, X_shortcut]) SKIP Connection

The skip connection is used before the RELU which brings the best outcomes.
ResNet-50 skip connections are made use of like the Fully Convolutional Network (FCN) and U-Net as well as to move information from previous layers to the next layers. The ResNet-50 model consists of 5 stages with 3 convolution layers and 3 convolution layers. It has 23 million trained variables as well.

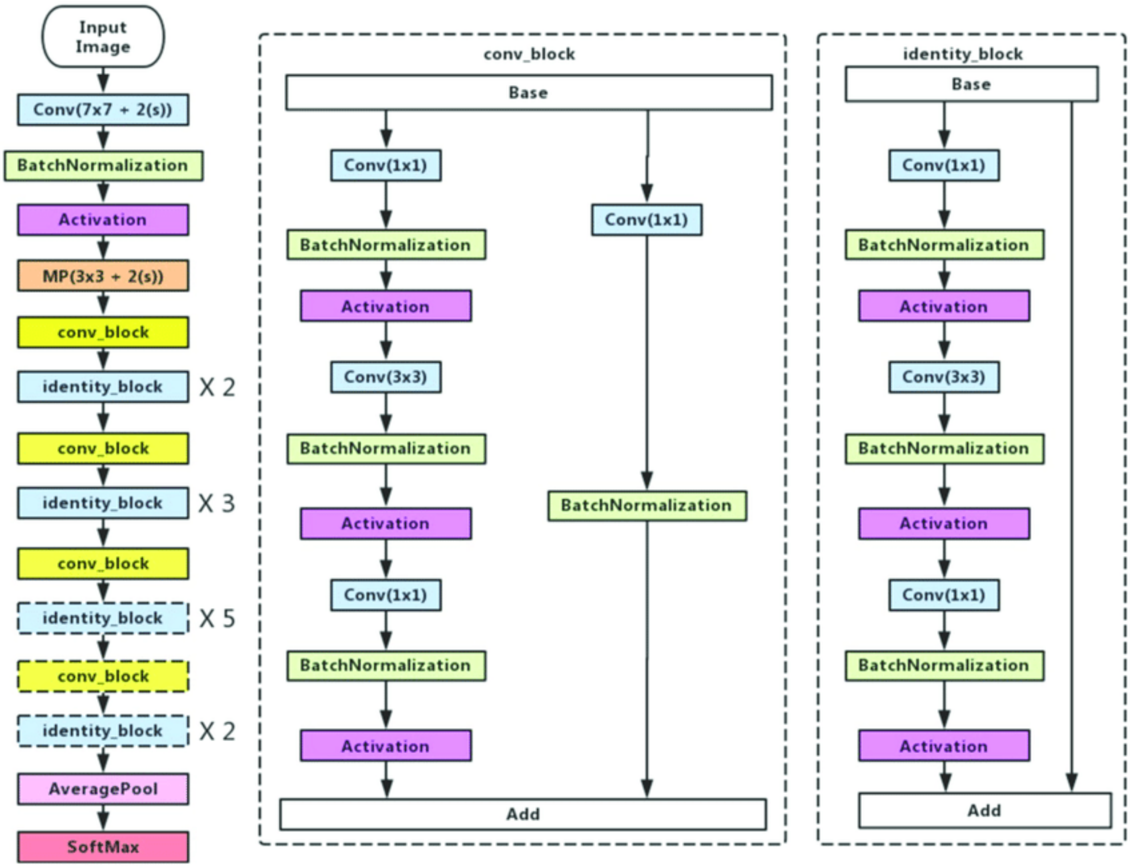

Figure 3.6: Resnet-50 architecture

In the left portion of the following figure is represented the ResNet50 architecture. In the middle section from the base section to Add section the layer transmission of conv 1*1 module is shown by which steps it can transfer and 2 layer block of only conv 1*1 and Batch Normalization. And in the right side, identity block which will not change the input extents.

3.4 MobileNet Architecture

The MobileNet is depth-wise separable filters that can be tuned to trade-off between latency and accuracy. The layer named for depth-wise Separable Convolution, factor to boost the recital. It is a form of factorized convolutions that factorize a standard convolution into a depthwise convolution and a 1111 convolution called a pointwise convolution. In MobileNet, the depthwise convolution applies a single filter of a 1111 convolution to every input channel for the aggregation of the outputs.

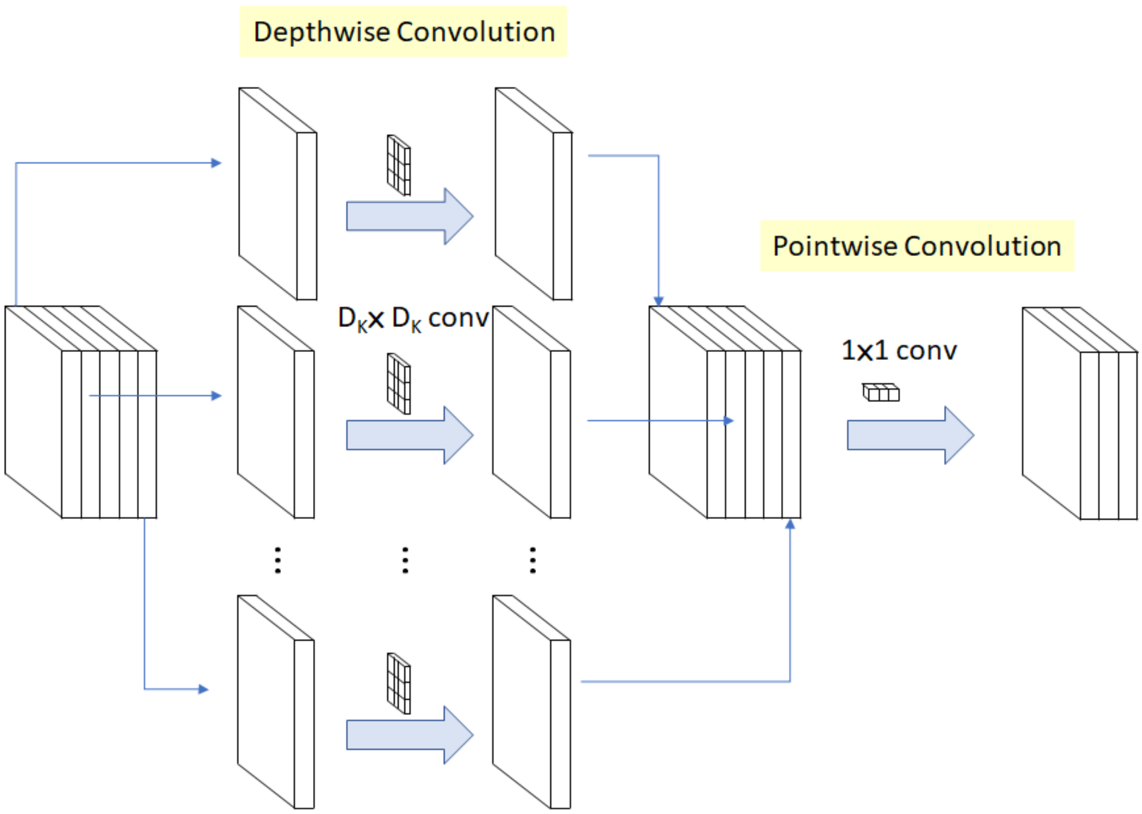

Figure 3.7: MobileNet framework-1

Chapter 4

Data sets

First, the image is acquired and the clustering method is used to segment the disease-affected areas. Then the feature extraction is performed on different disease cases of Tomato Bacterial spot, Tomato Early Blight, Late Blight, Leaf mold, Septoria leaf spot, spider mites two-spotted spider mite, target spot, yellow leaf curl virus, mosaic virus and tomato healthy.

In the first step of Image Acquisition, images are collected from the internet sources of Plantvillage tomato leaf data-set of 10 different Tomato leaf diseases.

In these collected images, various noises are present which are a hindrance to an accurate result. So that image pre-processing is used to increase by deleting noises from the given data. Image resize, filtering, image conversion, and contrast enhancement altogether hold the image processing method. By resizing and converting to a gray image, the image is converted noise-free through filtering. Then by segmentation the image part by part to evaluate the image through Resnet-50 and MobileNet Model, where clustering is used to segment.

For the minuscule differences, sometimes the output gives the erroneous result. So by deep learning methods will collect knowledge from two different sets of the same disease, but in a little change and learn in an accurate way and output precisely. The visualization of 10 paradigms in different cases are illustrated below.

Chapter 5

Results

The three models that showed the prospective for giving the best results for our classification problem are built and trained after further model optimization and parameter tuning using the methodology described in (chapter 4). The models are evaluated using confusion matrices and compared using the accuracy, precision and recall scores. We had 553 images in our test set that we fed to all three models and the results are discussed in this chapter. Below is the confusion matrix of the CNN model that we have generated to visualize and further analyze the outcome.

By using Fastai Rasnet-50 and MobileNet models, we run on the samples of the tomato leaf for several times trained through model optimization. The process of working is described in chapter 3. The two models result in inaccuracy are compared and judged by train loss, valid loss, error rate, accuracy and time. The Renset-50 model is also evaluated through the confusion matrix.

The confusion matrix of Resnet-50 model has been illustrated below to analyze the output more distinctly. Actual samples are drawn vertically and the ultimate result came diagonally of 10 X 10 confusion matrix.

Time	ms/step	loss	accuracy
138	876	.0142	.0060
118	746	0.0126	0.9963
125	790	0.0042	0.9988
126	796	0.0092	0.9970
125	790	0.0080	0.9973
128	813	0.0154	0.9958
129	816	0.0108	0.9971
130	825	0.0206	0.9947
136	859	0.0104	0.9976
141	890	0.0110	0.9968
132	836	0.0117	0.9967
122	770	0.0126	0.9970
121	767	0.0216	0.9946
125	88	788	6344

Table 5.1: MobileNet output data Table

5.1 Resnet-50 and MobileNet

From the above experimental results, it is clear that by deep learning process 99.81% accuracy in Resnet-50 and 99.88% in MobileNet method. So in the general sense, Resnet-50 is giving lesser results than MobilNet methodology. But Resnet-50 is mush complex architecture and robust than MobileNet.

Whereas MobileNet is lightweight and much simpler in architecture which can be easily executable from android device configuration. So MobileNet albeit efficient as simpler, it loses its efficiency in case of a large quantity of data. In that case, MobileNet not only takes less time but also works efficiently by giving an accurate result of disease detection which is our main objective of this whole paper.

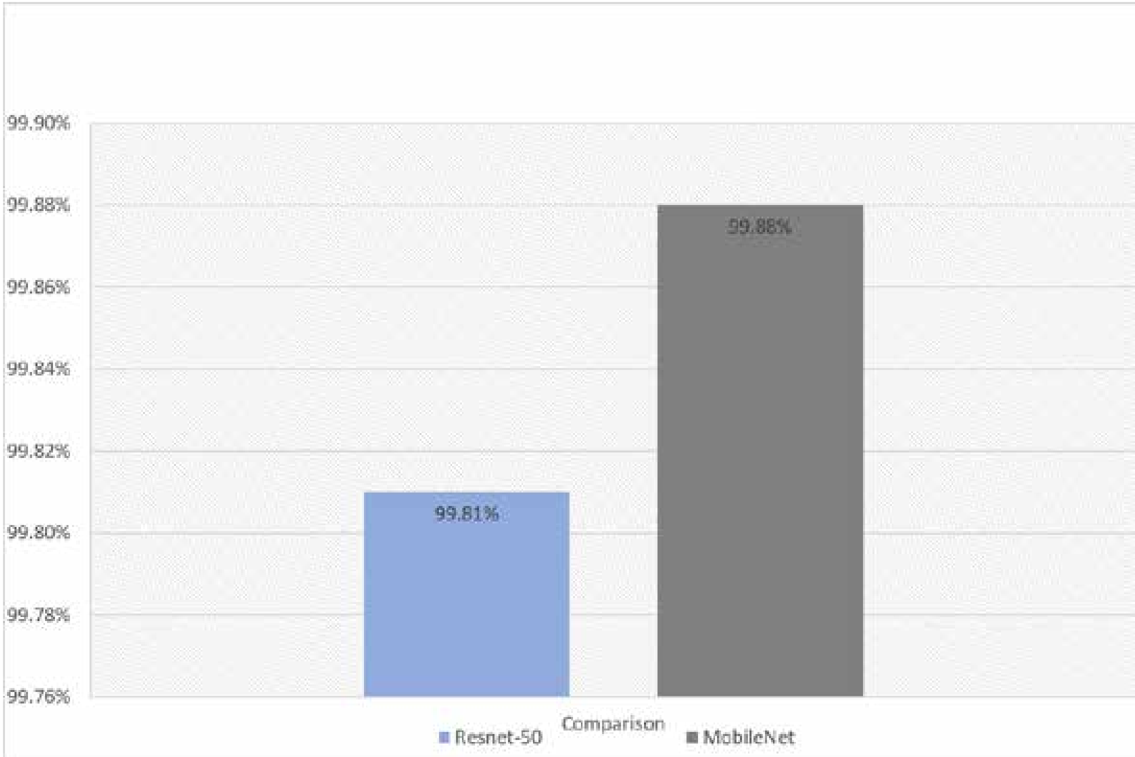

Figure 5.9: Resnet-50 and MobileNet Graphical Comparison

5.2 Comparison with other works

K-nearest neighbor (KNN) and multi-class Support Vector Machine (SVM) are compared in computer Vision-Based Detection And Classification of Tomato Leaf Diseases and maximum accuracy of 92% is obtained. Here, the knowledge-based technique is exercised to increase the process obtained to get a precise result. In comparison to this experiment, our result is a much better stage, though we used the knowledge-based deep learning technique by Resnet-50 and MobileNet as well.

In contrast, we achieve 99.81% accuracy in Resnet-50 and 99.88% in the MobileNet process. In the earlier experiment, the detection was only finding whether the disease is present or not. But in our experiment we judge accurately different kinds of diseases through deep learning, that is why it consumes much more time but in return gives more accurate results. That is why our method can play the most significant role in finding particular disease, by extending further disease studies, and eradicate through specific eradication which not only saves cost but also achieve efficacy in the agricultural sector.

Chapter 6

Conclusion and future works

Here the processes are used to data processing by Data transform, Data augmentation, and data splitting with training data visualization. We compare the disease finding through training loss, valid loss, error loss, accuracy data output by the Resnet-50 and MobileNet algorithm approaches. Here in Resnet-50 accuracy found in best is 99.81% and in MobileNet algorithm, in epoch 82 the result is 99.88% to the trained data. These results are a clear sign of finding disease by using visualization data in a very accurate way. From the results, we believe that these data visualization processes can be extended to further agricultural plants for leaf disease identification.

The experiments through Resnet-50 and MobileNet illustrate that the perception rate of finding disease is very precise. In succeeding, the suggested methods will be enlarged to concede and acknowledge the disease of any plants by means of leaves or any other parts of plants.

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