

Recognition of leaf blight and fruit rot diseases of Eggplant using Transfer Learning

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Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled “**Recognition of leaf blight and fruit rot diseases of Eggplant using Transfer Learning**”, submitted by Imdadul Haque(171-15-1440) and Shamima Akter(171-15-1200) and Md Lakibul Hasan(171-15-1276) to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 5th December,2020.

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We hereby declare that, this project has been done by us under the supervision of **MD REDUANUL HAQUE, Senior Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Eggplant is an essential food in Bangladesh because the majority of the population still live below the poverty line. Eggplant is so inexpensive that it helps poor people to meet the demand of food. In other words, we can say eggplant helps to fulfill one of the basic needs (food) of humans. But a large quantity of eggplant production faces a huge loss because of eggplant's leaf blight and fruit rot diseases. Many types of leaf blight and fruit rot diseases reduce the healthy growth of eggplant seedlings and fruits. Due to lack of technology and education in Bangladesh, many farmers are still unable to diagnose the disease properly. As a result, it is harmful for both economic development and poor people. So, we proposed our work that can detect the leaf blight and fruit rot diseases of Eggplant very accurately. We use MobileNet, CNN, Multilayer Perceptron & VGG16 for our work. MobileNet, CNN, Multilayer Perceptron, VGG16 help us to enhance the object detection result. These methods are very helpful to detect eggplant disease. MobileNet gives accuracy 95%, CNN gives accuracy 81%, Multilayer Perceptron gives accuracy 77% & VGG16 gives accuracy 70%. The accuracies are pretty good, MobileNet gives the best accuracy among the other methods. Hence this work will help to increase the economic development and eggplant production, reduce the food shortage of the poor and the grief of the farmer.

Keywords: Deep Learning, Transfer Learning, MobileNet, CNN, Multilayer Perceptron, VGG 16, Eggplant Disease.

TABLE OF CONTENTS

CONTENTS	PAGE
Board of examiners	ii
Declaration	iii
Acknowledgements	iv
Abstract	v
CHAPTER	
CHAPTER 1 : Introduction	10-14
CHAPTER 2 : Literature Review	15-19
CHAPTER 3 : System Architecture	20-21
CHAPTER 4 : Methodology	22-28
4.1 Transfer Learning	22-23
4.2 MobileNet	23-25
4.3 CNN	25-26
4.3.1 Convolution Layer	26
4.3.2 ReLU Layer	26
4.3.3 Pooling Layer	26
4.3.4 Fully Connected Layer	26
4.4 ImageDataGenerator	26-27
4.5 Multilayer Perceptron	26
4.6 VGG 16	27-28
CHAPTER 5 : Implementation	
5.1 Implementation	29-32
5.2 Dataset Description	29-32
	32

CHAPTER 6 : Experimental Results and discussions	33-34
CHAPTER 7 : Conclusion	35
7.1 Limitations	35
7.2 Future Scope	35
7.3 Conclusion	35
REFERENCES	36-37

LIST OF FIGURES

FIGURES	PAGE NO
Figure 1: Four types of BT-Eggplant	11
Figure 2: Infected eggplants leaves and fruits.	13
Figure 3 : System Flowchart 22	20
Figure 4: Architecture of MobileNet	23
Figure 5: Shape of function	24
Figure 6: Number of blocks with channels.	24
Figure 7: CNN(Convolutional Neural Network)	25
Fig 8: VGG16 Architecture	28
Figure 9: Equation	29
Figure 10: Feature Extraction	29
Figure 11: Eggplant classification	30
Figure 12: Confusion Matrix	30
Figure 13: Experimental images	33

LIST OF TABLES

TABLES	PAGE NO
Table 1: Literature Review	15-17
Table 2.1: Accuracy	33

CHAPTER 1

Introduction

Eggplant is a plant that bears purple, soft, permeable fruit. In South Asia it is known as “Brinjal”. There are two types of shapes in eggplant fruit; long-shaped eggplant & round-shaped eggplant. Eggplant fruit can be purple, green and white in color. Color actually varies origin to origin. This fruit is actually a vegetable and we use it for cooking purposes. In the botanical section, it is defined as berry. The Eggplant flower is not edible and it is purple to white in color. Eggplant’s stalks are often softly spiky. And a healthy eggplants leaf is green in color. A full grown up plant can be 40 cm to 150 cm in height.

It is a belief that eggplant originated in India or in Africa [1]. Therefore, in Bangladesh we have BT (four types) and non-BT Eggplant. Four types of BT Eggplant names are: Bari BT Brinjal–1 (Uttara), Bari BT Brinjal–2 (Kajla), Bari BT Brinjal–3 (Nayantara) & Bari BT Brinjal–4 (Iswardi/ISD006). BT Eggplant is genetically modified. BT-Eggplant is developed because non-BT Eggplant caused various production damages and loss. Non-BT Eggplant gets easily affected by bugs and insects. So, BT-Eggplant is developed and it is superior to non-BT Eggplant. BT-Eggplant helps poor farmers to produce more healthy fruits without any types of pesticides or chemicals.

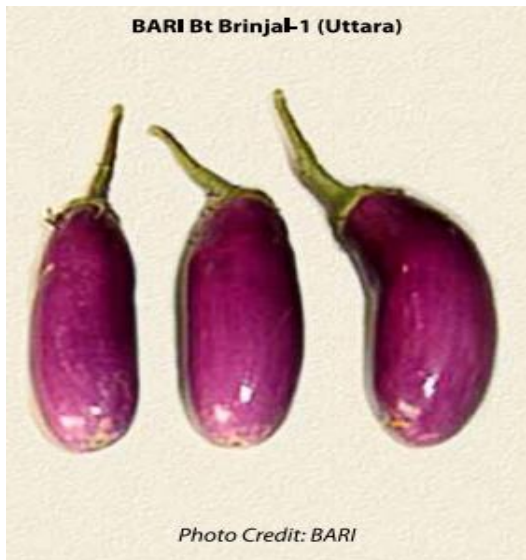




Figure 1: Four types of BT-Eggplant

Eggplant is second in the list of crops production in Bangladesh because it is very common and inexpensive in the country [2]. More than 30,000 farmers grow eggplant in Bangladesh [3]. During 2012-2013, in 50,000 hectares area 345,000 metric tons eggplants were produced. During 2016-2017, in 45,665 Acres area 159,891 metric tons eggplants were produced. During 2017-2018, in 45,760 Acres area 160,145 metric tons eggplants were produced. During 2018-2019, in 47,213 Acres area 170,189 metric tons eggplants were produced. The profit is BDT 6.63 in per Kg, net return is BDT 303,358 per hectares and cash margin is BDT 345,415 per hectares [4]. Eggplant is planted by farmers approximately 10% of the total area of vegetables cultivating land in Bangladesh.

Though botanists are trying hard continuously to improve the immunity of eggplant, there are still many diseases that are causing fatal losses of eggplant production. “Damping-off”, “Bacterial wilt”, “Phomopsis fruit rot” are major diseases of eggplant in Bangladesh. Because of Damping-off disease, poor quality seedlings grow from seeds. This disease is created from seed and soil fungi. The fungi can outlive for a long time in the plants and soil. Because of this disease, young seedlings root and leaves become dark and make water-soaked wounds. As a result, the plant's leaves fall off. Bacterial wilt is the most ravenous disease which intensity is 10-90%. Bacterial wilt occurred soon after the seed’s planting and it may continue till the final harvest. Phomopsis fruit rot not only damages fruit, it damages leaves and stalks also. Because of this disease, fruits become

discolored, brown and waterish. And if fruits become dry, it continues to become drier and finally become like black mummies. Phomopsis makes leaves yellow and dry. If phomopsis infected the stalks root, then the stalks can die. Phomopsis decreases the growth rate of plants from 15 to 50% [5]. There are some other diseases also. They are “Cercospora Leaf Spot”, “Alternaria Rot”, “Anthracnose Fruit Rot”, “Fusarium Wilt”, “Verticillium Wilt”, “Phytophthora Blight”, “Southern Blight” [6]. “Cercospora Leaf Spot” is a fungal disease. It only affects the stalks and leaves. At first in the leakages small and yellow wounds are shown. Because of this disease the fruits become smaller. And the speciality of this disease is that it survives in the winter and in spring the affected seeds spread through animals, humans, wind and rain. This disease is also called “frog eyes”. “Alternaria Rot” disease causes gray, water-soaked wounds into fruits. Because of this disease the seedlings become odd shaped. This disease can occur both in mature and immature eggplant fruits. “Anthracnose Fruit Rot” disease occurs in ripe fruit. Sometimes it hides into unripe fruits and shows after the fruit is ripe. This disease causes orange or pink patches into fruits. “Fusarium Wilt” harms the leaves of eggplants. Sometimes from one leaf the whole plant can die. “Verticillium Wilt” disease is created from soil bacteria. It creates V-shaped wounds into leaves. This dries up the seedling and causes the seedling to eventually die. ” Phytophthora Blight” disease first occurs in the roots of plants. Then day by day it spreads in fruits and leaves. And it creates dark green wounds. “Southern Blight” is a fungal disease. It can occur in both immature and mature plants. It creates brown wounds into plants.

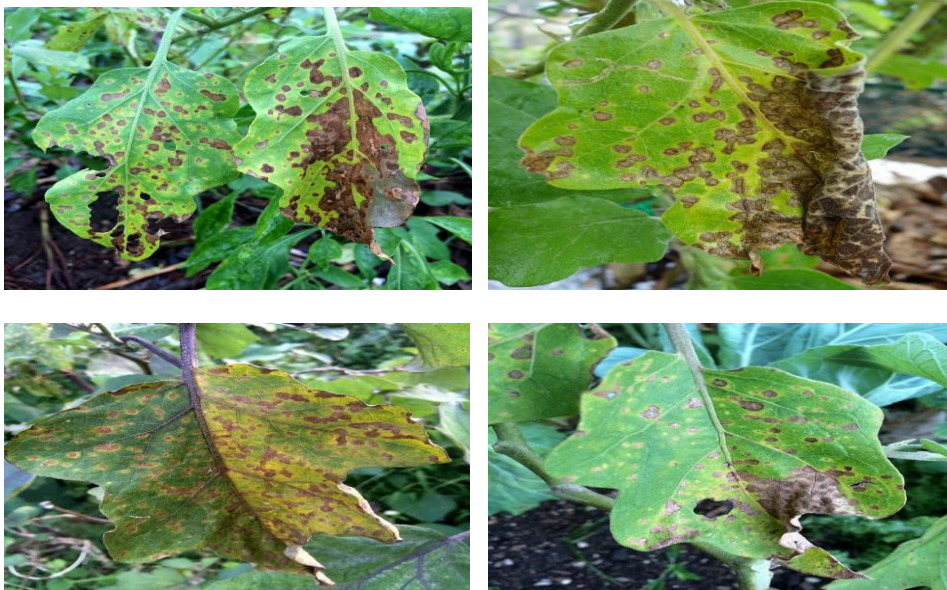




Figure 2: Infected eggplants leaves and fruits.

From 2016-2019, due to flood and excessive rain damage production loss is 6035 M. Ton. Total yield losses in Bangladesh up to 86%. In BT Eggplant, fruit nuisance rate is 0-2,27% in 2016 and 0% in 2017. In non-BT Eggplant, fruit nuisance rate is 36.70% in 2016 and 45.51% in 2017 [7]. In Bangladesh, rural farmers cannot detect disease with modern technologies because they still rely on traditional old knowledge. They just guess that the seedlings are affected, and give the same medicine, pesticides, chemicals to the seedlings, whereas every eggplant disease has its own medicine. In plant clinics and agricultural offices, every farmer cannot access the facilities because of poverty.

Except this, field officers cannot always serve the information to the farmers which leads them to resolve this problem. Hence, lack of information to the farmers leads them to revert back to the traditional places. As a result, the production rate of eggplant is decreasing drastically in Bangladesh. Some studies show that the general source of information of farmers is other farmers but for complex and technical matters, farmers prefer first-hand information from experts. That's why a specified medium should be applied in this situation. Now we need to focus on this increasable problem.

Our system is robust as well as effective for early detection of eggplant disease. There are some bacterial and contagious illnesses that can strike eggplant patches, causing imperfect natural products, defaced foliage, diminished creation and now and then plant death. To distinguish these microorganisms, it tends to be testing a direct result of their equivalent looking. Neighborhood helpful augmentation administration can endorse a plant pathology lab to certify a specific assurance through a submitted test. Yet, paying little heed to which illnesses may be standing ready, with regards to eggplants. But when the question is about cureness it needs to be solved quickly in an effective way through ICT (Information and Communication Technology). Many international Agricultural organizations are now promoting Information and technology in the agricultural sector.

This IT based agricultural system can ensure the fastest communication of agricultural plant disease information among farmers.

This study aimed us to develop a model that is based on transfer learning that can recognize the blight of leaf and disease of fruit rot of Eggplant.

Actually, that transfer learning is based on one of the machine learning method where a specific model implemented for a task which is reused as the beginning stage for a model on a second related task. This model becomes very famous because not only it can train deep neural networks but also little data. That's why it is also very useful in data science. Now this question arrives at how this model is so effective in our problem which is given in the title. In transfer learning, machines utilize the knowledge which is gained from a specific task. By using a huge dataset of eggplant leaf we will train the model as a pre-trained model. Then that model can identify the specific disease from a random image.

This posterior paper is designed as follows: In Chapter 2: Briefly describe the literature review point of this related project work, Chapter 3: System Architecture, Chapter 4 provides the inside methodology, Chapter 5 introduces the implementation of this model. Chapter 6 describes Experimental Results and description & Chapter 7 describes the Conclusion.

CHAPTER 2

Literature Review

Table 1: Literature Review

TITLE	AUTHOR	METHOD	ACCURACY
i.Disease classification in Solanum melongena using deep Learning	KR Aravind <i>et al.</i>	Deep Learning method (CNN), VGG16, AlexNet	96.7%

ii. Mobile-Based Eggplant Diseases Recognition System using Image Processing Techniques	Jake Guabes Maggey	CNN, ModileNetV2, images Processing Techniques	Not defined
iii. Spectrum and Image Texture Features Analysis for Early Blight Disease Detection on Eggplant Leaves	Chuanqi Xie and Yong He.	KNN and Adaboost classification model	88.46%
iv. Relevance of hyperspectral image feature to catalase activity in eggplant leaves with grey mold disease	Xie, <u>Chuanqi</u> <i>et al.</i>	Partial least squares regression (PLSR), least squares support vector machines (LS-SVM) and BP neural network (BPNN)	Not defined
v. Identification of Eggplant Young Seedlings Infected by Root Knot Nematodes Using Near Infrared Spectroscopy	Wei Ma <i>et al.</i>	MSC and SG pretreatment method, Principal component analysis (PCA).	90%

vi. Plant Leaf Disease Detection Using Adaptive Neuro-Fuzzy Classification (<i>Tomato & Brinjal</i>)	Hiteshwari Sabrol, Satish Kumar	GLCM matrix, ANFIS based classification model	90.7% & 98.0%
vii. Early Detection of Botrytis cinerea on Eggplant Leaves Based on Visible and Near-Infrared Spectroscopy	D. Wu, L. ng, C. Zhang, Y. He	Back-propagation neural networks (BP-NN), Principal component analysis (PCA)	85% , 70%
viii. Disease Classification in Eggplant Using Pre-trained VGG16 and MSVM	Aravind Krishnaswamy Rangarajan; Raja Purushothaman	VGG16, MSVM	99.4%
ix. Deep Learning Based on NASNet for Plant Disease	Adedamola Adedoja; Pius Adewale Owolawi; Temitope Mapayi	Deep learning based NASNet architecture using transfer learning algorithm	93.82%
x. Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification	Srdjan Sladojevic; Marko Arsenovic; Andras Anderla; Dubravko Culibrk; Darko Stefanovic	CNN, OpenCV	96.3%.

xi. Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques.	Marwan Adnan Jasim; Mustafa Jamal AL-Tuwaijari	Image Processing, CNN	98.29% for training, and 98.029% for testing
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In Aravind, K. R., Raja, P., Ashiwin, R., & Mukesh, K. V. (2019) , they worked on Solanum Melongena using deep learning. They used CNN, VGG16 and AlexNet. Their accuracy was about 96.7% [8].

In Maggay, J. G. (2020) , they prepared a mobile based eggplant disease recognition system using Image Processing. They used CNN, MobileNetV2. Their accuracy is not defined [9].

In Xie, C., & He, Y. (2016) , they researched about early blight disease of eggplant leaves with spectrum and texture features. They used KNN (K-Nearest neighbor) and AdaBoost classification models. The models achieve CRS (Classification rates) over 88.46%. In their work, they acquire hyperspectral images by covering wavelengths. Then they identified gray images pursuant to wavelengths. Then they extracted texture features by GLCM (gray level co-occurrence matrix) from hyperspectral and gray images. Their work exhibited that spectrum and texture features were effective for early blight disease detection on eggplant leaves [10].

In Xie, C., Wang, H., Shao, Y., & He, Y. (2015) , they found relevance of hyperspectral image feature to activity in eggplant leaves with grey mold disease. They used PLSR (partial least squares regression), LS-SVM (least squares support vector machine and BPNN. Their accuracy is not defined [11].

In Wei Ma et al. , they used infrared spectroscopy to identify root knot nematodes in eggplant young seedlings. They used the MSC and SG pretreatment method. They achieved accuracy above 90% [12].

In Hiteshwari Sabrol et al., Satish Kumar et al., they did classification of different types of diseases of eggplant and tomato. The diseases- recognized by texture patterns. They used a GLCM matrix to compute the features.

They used the ANFIS based classification model for disease recognition by classification. The ANFIS gives accuracy of 90.7% and 98.0% [13].

In Wu, D., Feng, L., Zhang, C., & He, Y. (2008) , they applied visible and near-infrared reflectance in eggplant leaves before the Botrytis Cinerea disease appeared for early detection. They executed principal component analysis. They used the BP-NN (back-propagation neural network) model which gave 85% accuracy in predicting fungal infections. Then they executed partial least squares regression, after this the accuracy of BP-NN model was 70%. Thus their study showed that visible and near-infrared spectroscopy can apply for early detection of Botrytis cinerea on eggplant leaves [14].

In Rangarajan, A. K., & Purushothaman, R. (2020) eggplant disease classification models, the keras module VGG16 is used for feature extraction and VGG16 supports 244x244 pixels images. So after converting the images into 244x244 pixels, MSVM(Multi-Class Support Vector Machine) is used for classification the images and after classification it provides 99.4% accuracy [15].

In Disease, D. L. (2019) a plant disease recognition system using leaves image model is implemented, they are mainly used deep learning based NASNet architecture using transfer learning algorithm and also classify the plant leaves either not disease or disease. For classification disease they have used 54,306 images with fixed sizes 256x256 and have gotten 93.82 % accuracy [16].

In Sladojevic, S., Arsenovic, M., & Anderla, A. (2016) automatically plant disease based on leaf images classification of between healthy leaves and 13 different types of disease and before training the dataset it automatically resizes the image into 256x256 using OpenCV framework and the background image dataset are basically taken from Stanford background dataset . Now 30880 and 2589 images are used for training and validation of the model and it precision the accuracy between 91% to 98% and on average it provides 96.3% accuracy [17].

In Jasim, M. A., & AL-Tuwaijari, J. M. (2020) plant leaf (tomatoes, pepper, and potatoes) disease detection and classification system is completed by using image processing to resize the image data into 128x128 and then CNN is used for training and testing the model. Here total 20636 images are included and 12 classes are used for disease and 3 classes are for healthy leaves and totally 15 classes are classified. After the training it reached 98.29% accuracy and 98.029% accuracy for testing [18].

CHAPTER 3

System Architecture

Deep Learning based architecture research project for classification of eggplant disease as leaf blight and fruit rot disease of fresh eggplant means there is no disease in eggplant as absent of leaf blight and fruit rot disease. We mainly do for farmers so that they can improve their eggplant cultivates for using our techniques as leaf disease and rot disease detection and this is important that we made a comparative research project where we have used four different deep learning algorithms and that's are mobileNet, CNN (Convolutional Neural Network), VGG16 and MLPs (Multi-Layer Perception). We can do it successfully do it for choosing best algorithms among mobileNet, CNN, VGG16, MLPs. We have able to find the better algorithm for performing to detect eggplant disease and the mobileNet performs too better than others three algorithms and for every algorithms we have used same dataset and used 100 epochs for training eggplant dataset.

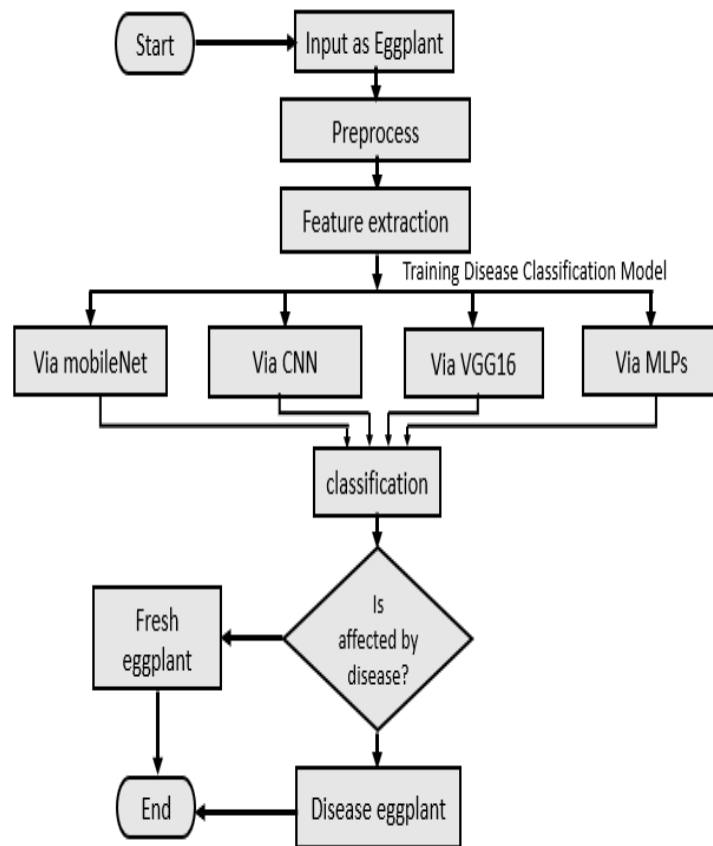


Figure 3 : System Flowchart

The flowchart defines whole disease classification system using four different types of algorithms are mobileNet, CNN, VGG16 and MLPs. After starting the model, we need the eggplant dataset where is included fresh eggplant and rot disease and leaf disease data and then in preprocess section, we just prepared the dataset for our model. Because we have used different types of eggplant image data but we need to convert all the image into a single size of image dataset where all the image data will be converted as 224x224. The we extract the feature of image data and for extract the image we have used max_pooling in mobileNet and CNN model and for VGG16 classification model VGG16 is used for feature extract. Now after the feature extraction we are training our model via mobileNet, CNN, VGG16 and MLPs for classification of our eggplant disease detection model. And with respect to classification model, it will be converted into two categories as fresh eggplant or disease affect eggplant

CHAPTER 4

Methodology

In this work, we will implement, explore and influence various transfer learning based Architectures and also dataset characteristics that is at the point when we need all the more preparing information or better models for object detection purpose, MobileNet, CNN, ImageDataGenerator, VGG16, Multilayer Perceptron.

4.1 Transfer Learning

CNN (Convolutional Neural Network) can be designed from scratch and earlier trained on various datasets to acquire better performance. This approach demands a lot of time, even if it is done by high demanded hardware resources. Although it is implemented in this paper. Transfer learning is one of the machine learning based methods where a model produced for an undertaking from the beginning stage dependent on a subsequent task. The point of transfer learning is to become familiar with an item prescient capacity for a particular task. This could be occurred by the target domain as well as other source domain and source tasks. The principle thought behind transfer learning is taking a model that has just been utilized and furthermore repurposing it for another task. Actually, in this transfer learning, we usually try to transfer knowledge to maximum possible ways from the previous task the model was trained on to the new task at hand.

As there are three types of approaches that work in transfer learning, we select the pre trained model among 1. Training a model, 2. Using a pre-trained model and 3. Feature extraction method.

Actually a pre-trained model is used here as the starting point on computer vision. We used Keras that provides nine pre-trained models for transfer learning and it's working method such as prediction, feature extraction and fine-tuning [19]. Among published literature (e.g. VCG, Inception V3, ImageNet, MobileNet) that are used for the less computational cost of training season. Those models are commonly practiced to import and use other types of models. We will use MobileNet as a pre-trained model to save our computational power and resources. The equipment utilized for doing the examination has the accompanying setup:

OS: Windows 10

GPU: 4GB NVIDIA 940MX

RAM: 8GB

4.2 MobileNet

MobileNet is a smoothed out design that utilizes profundity shrewd distinct convolutions to develop lightweight profound convolutional neural organizations and gives an effective model to portable and inserted vision applications. The structure of depthwise separable MobileNet is shown in Figure 1.

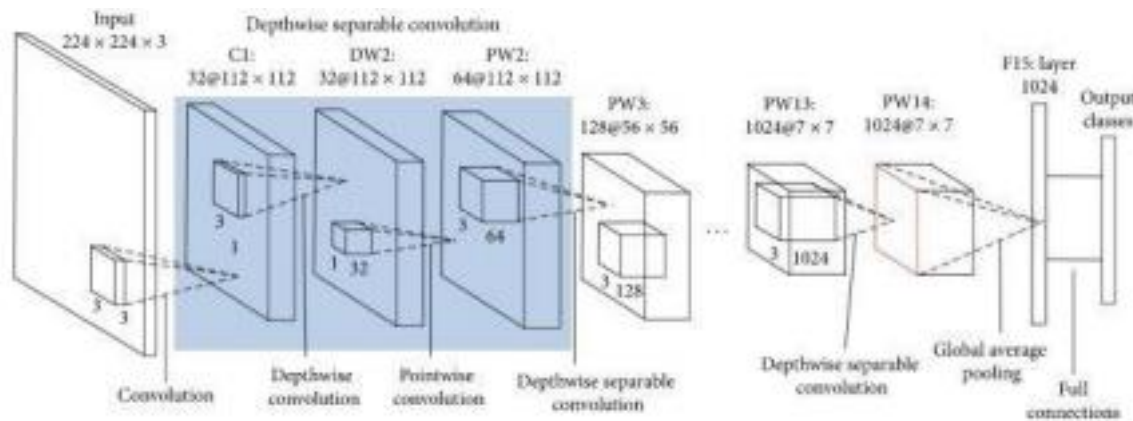


Figure 4: Architecture of MobileNet [20]

MobileNets are a group of versatile first PC vision models for TensorFlow, intended to successfully expand precision while thinking about the limited assets for an ondevice or implanted application [21]. It is less sized and less latency, less power models to meet the device resource liabilities. Actually for classification, embedding, segmentation and detection purposes this model is being created. MobileNet is designed by Google researchers. It's a class of convolutional neural networks. As "mobile-first," they are asset agreeable and they run quickly on cell phones [22]. One of the boundaries of MobileNet are Width multiplier and resolution multiplier that may be performed to weigh the resource-accuracy tradeoff. The width multiplied can slim the network while the resolution multiplier can change the information picture measurement. These changes can decrease each layer's internal structure [23]. The latest mobileNet version 2 is recently released by google. MobileNet V1 depended on convolutional layers which is basic for computer vision tasks. But one of the main limitations of MobileNet V1 was its quite expensive computational cost. This can be supplanted by supposed depthwise distinct convolutions.

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The work of the convolution layer is part into two subtasks: first one is, there is a specific depthwise convolution layer that channels the information, trailed by a 1×1 pointwise convolution layer that consolidates these separated qualities to make new highlights. But in present day structures, the convolutional layers are followed by batch normalization. The actuation work utilized by MobileNet as well as ReLU6. It prevents the actions from becoming too big which is describe in following structure [24]:

$$y = \min(\max(0, x), 6)$$

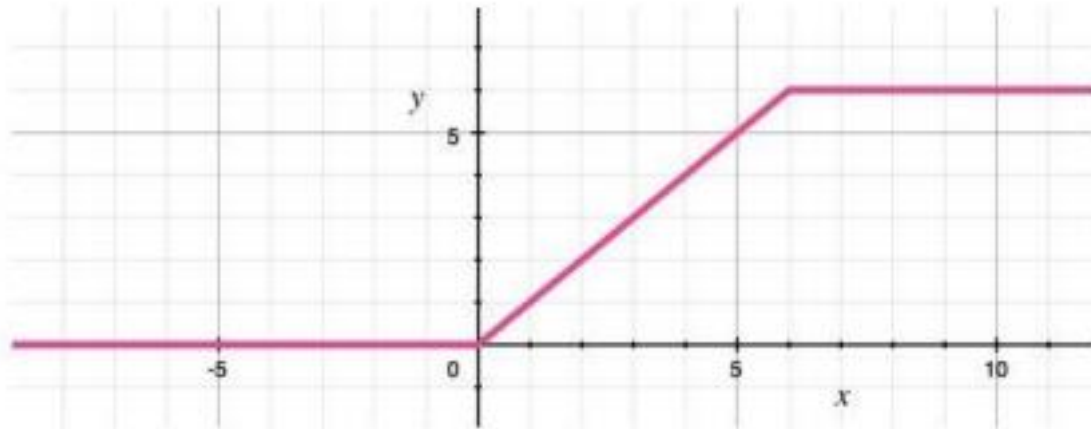


Figure 5: Shape of function [24].

But the latest MobileNet V2 still uses disting convolutions. It's building block's figure defines how a function travels over the 1×1 Expansion Layer to ReLU6 then 3×3 Depthwise Convolution to ReLU6 and then 1×1 Projection Layer to Batch Normalization.

We are motivated to use MobileNet V2 because of its remaining associations and the grow/projection layers. In Figure 6 we will observe how many channels stay between the blocks.



Figure 6: Number of blocks with channels.

After re-train the classifier of our dataset for object detections we used the base network as feature extraction.

4.3 CNN

CNN(Convolutional Neural Network) is a combination of Artificial Neural Networks and a set of operations (Convolutions). CNN is composed of artificial neurons. The artificial neurons simulate biological neurons. In easy words we can say that, how humans perceive an image into his different layer of brain is the study of CNN. When humans and mammals see something, they capture the scene then process it layer by layer with their neurons. After processing they detect the object then give the best result. CNN works exactly like that. It processes the image layer by layer then detects the object. It works like Artificial Neuron.

CNN consists of Convolution Layer, ReLU Layer, Pooling Layer and Fully Connected Layer.

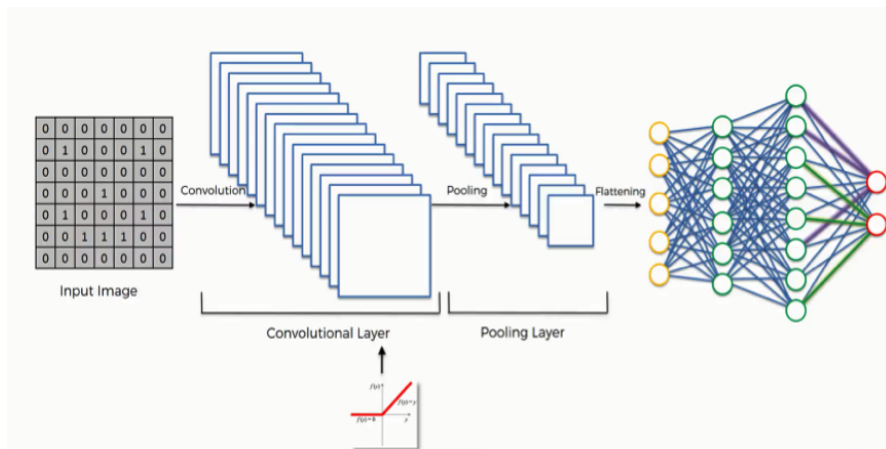


Fig 7: CNN(Convolutional Neural Network)

$$Y = f \left(\sum_{i=1}^n x_i * w_i + b \right) \dots \dots \dots (1.1)$$

In this formula (1.1), f is the activation function of neurons. x is the set of inputs. w is the set of weights. b is bias. The letter Y represents the output which is a function that applied to the input weighted by all these elements are inside weights plus the bias. Thus we will have a single output that we are recalling the artificial neural.

Convolution in images is processed by multiplication the input window with filter mask Kernel template. The filter mask Kernel template window is,

- w(-1,-1) w(-1,0) w(-1,1)
- w(0,-1) w(0,0) w(0,1)
- w(1,-1) w(1,0) w(1,1)

4.3.1 Convolution Layer

Convolution layer is a layer which filters images and sends it to the pooling layer. Convolutional layer has three hyperparameters. These parameters control the size of output volume. These parameters are : depth, stride & zero-padding. To calculate the number neurons in a volume, the formula is :

$$((W-K+2P)/S) + 1 \dots\dots\dots(1.2)$$

In this formula (1.2), W is the input volume size, K is the kernel field size, P is the amount of zero padding, S is the stride.

4.3.2 ReLU Layer

ReLU(Rectified Linear Unit) works after the Convolution Layer activation. It is an activation function. ReLU Layer removes negative values. Then it set zero in place of the negative values. ReLU function is very important. Because it doesn't saturate. And it works very fastly and easily.

4.3.3 Pooling Layer

Pooling Layer is non-linear and down sampling. In the pooling layer, the convolution layer sends the patch of image in half. Pooling reduces complexity. It also avoids overfitting. There are two types of pooling whose are Max pooling and Average pooling.

4.3.4 Fully Connected Layer

In a fully connected layer, the image will be sent through the convolution and pooling layers. And this layer's every node is connected to each node. That's why it is called a fully connected layer.

4.4 ImageDataGenerator

It is also called data augmentation. Actually, as a matter of fact it's a system that empowers specialists to significantly increase the diversity of data accessible for training models, without collecting the new data. In our work this data augmentation term refers to trimming, padding, and horizontal flipping of images. This can be commonly used in large neural networks. We used keras for this. It gives a particular ImageDataGenerator class that incorporates capacities of: (1) Sample-wise normalization, (2) Feature-wise normalization, (3) ZCA brightening. (4) Random rotation, shifts, shear and flips, (5) Dimension reordering, (6) Save augmented images to disk. During the training phase of the model, we only used synthetic images.

4.5 Multilayer Perceptron

Recently the interest of this multilayer Perceptron increases as classifiers in pattern recognition problems. The field of artificial neural networks is frequently called neural networks or multi-layer perceptron after possibly the most significant kind of neural networks. A perceptron is a single neuron model that was a precursor to greater neural networks.

Multilayer perceptron has multiple layer including only one input layer, one output layer and one or more hidden layer. It is used in ANN (Artificial Neural Network) and simple regression problems for bringing out interpretation from inexact and complex data that is used to extract models and discover trends which is way too complicated for human to understand.

Basically, Multilayer Perceptron (MLP) is an enhancement of feed forward neural network. The main uses field of MLP are in pattern grouping, acknowledgment, forecast and furthermore approximation.

This calculations occurring at each neuron in the yield and shrouded layer are as per the following,

$$(1) \text{ } ox = Gb2+W2hx$$

$$(2) \text{ } hx = \Phi x = sb1+W1x$$

predisposition vectors are $b(1)$, $b(2)$; weight matrices are $W(1)$, $W(2)$ and the activation functions are G and s . The arrangement of boundaries to learn is the set $\theta = \{W(1), b(1), W(2), b(2)\}$. Regular decisions for s include tanh function with $\tanh(a) = (e^a - e^{-a})/(e^a + e^{-a})$ or the calculated sigmoid method, with sigmoid $(a) = 1/(1 + e^{-a})$.

4.6 VGG 16

The VGG network architecture was at first proposed by Simonyan and Zisserman [25]. Essentially this is utilized for huge scale Image Recognition. The model achieves 92.7% top-5 test precision in ImageNet, which is a dataset of in excess of 14 million pictures having a spot with 1000 classes. VGG 16 is a CNN (Convolutional Neural Network) model which has 16 convolutional layer with 3x3 kernels also with a step of 1 and cushioning of 1 to guarantee of every actuation map holds a similar local measurement as the past layer. A corrected direct unit (ReLU) actuation is performed just after every convolution furthermore, a maximum pooling activity is utilized toward the finish of each square to lessen the spatial measurement.

It is used in large-scale image classification. For comparison with our proposed model we show the Simonyan and Zisserman [26] model.

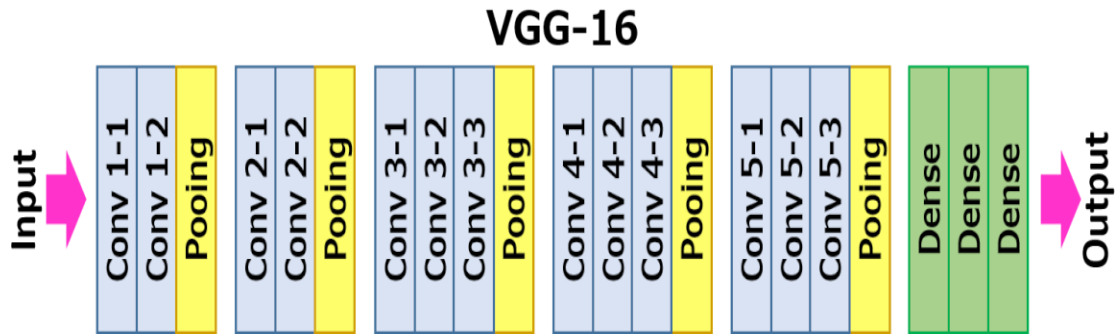


Fig 8: VGG16 Architecture

As a result of its significance and number of completely connected nodes, VGG16 is over 533MB. This makes passing on VGG a repetitive task. VGG16 is used in various significant learning image classification issues; more unassuming organization models are much of the time additionally appealing, (for instance, SqueezeNet, GoogLeNet, etc).

A drawback of the VGG16 model is that it is costly to assess and utilize a great deal of memory and boundaries. A large amount of these limits are in the completely connected layers, that are supplanted by a SVM classifier in our model, fundamentally lessening the quantity of vital boundaries.

CHAPTER 5

Implementation

5.1 Implementation

In this section we are discuss about the implementation process of using deep learning algorithms for performing on our eggplant image dataset. We also discuss about accuracy, recall, precision, f1 score from the confusion matrix with different algorithms and below the rules of accuracy, recall, precision and f1 score,

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \text{ --- (i)}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \text{ --- (ii)}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \text{ --- (iii)}$$

$$f1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \text{ --- (iv)}$$

Figure 9: Equation

We have used most useable four deep learning algorithms to predicts disease of eggplant and with better accuracy and below the part of feature extraction after taking the input image and preprocess of image dataset.

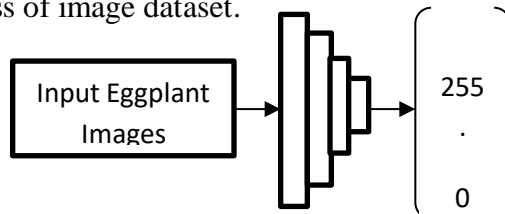


Figure 10: Feature Extraction

In flowchart section I have discussed about the feature extraction of image dataset and that is first of all we need to take image of eggplant as input image and then we need to preprocess of an image and preprocess section, we mainly resize of the image input because there is different size of image in our eggplant image dataset.

And we have converted in a single size all of the images as 224x224. After the feature extraction we have used the mobileNet for making a classification model to classify eggplant disease and fresh eggplant and there mainly performs some layer of mobileNet dense layer, softmax function of activation layer which works before the output and classifies the images either fresh leaves neither disease affected leaves as rot disease and leaf disease of eggplant in Figure-13.

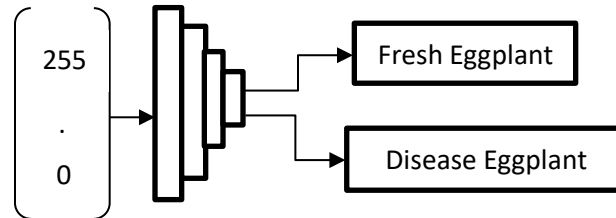


Figure 11: Eggplant classification

Now for CNN (Convolutional Neural Network) is also performs in hidden layer for classification and before classification first of all preprocess and image resize for making a single size of all images in Figure-10. Then Classification is done in Figure-11. And now for VGG16 which is a keras API modules also after preprocess the eggplant image dataset it also converted in a same size of all images and that is 224x224 done the classification using keras techniques. Now the MLPs (Multi-Layer Perception), deep learning algorithm is used for making the prediction systems and also successfully done it. Totally, we have used 100 epochs for training our model so that our model train more efficiently and also able to predicts more perfectly. Below the confusion matrix all of the Deep Learning algorithm as mobileNet, CNN, VGG16, MLPs,

<table border="1"> <tr> <td>107</td> <td>6</td> </tr> <tr> <td>3</td> <td>44</td> </tr> </table>	107	6	3	44	<table border="1"> <tr> <td>104</td> <td>38</td> </tr> <tr> <td>6</td> <td>12</td> </tr> </table>	104	38	6	12	<table border="1"> <tr> <td>110</td> <td>50</td> </tr> <tr> <td>0</td> <td>0</td> </tr> </table>	110	50	0	0	<table border="1"> <tr> <td>124</td> <td>36</td> </tr> <tr> <td>0</td> <td>0</td> </tr> </table>	124	36	0	0
107	6																		
3	44																		
104	38																		
6	12																		
110	50																		
0	0																		
124	36																		
0	0																		
mobileNet	CNN	VGG16	MLPs																

Figure 12: Confusion Matrix

Although we have used same dataset and same format of eggplant dataset but there are different confusion matrix for different deep learning as mobileNet, CNN, VGG16 and we used different format of eggplant dataset but used in same eggplant dataset with same number of data in MLPs.

From the deep learning algorithm's confusion matrix, we can find the accuracy, recall, precision, f1 score using above equation (i), (ii), (iii), (iv).

From mobileNet algorithm's confusion matrix,

$$Accuracy = \frac{107 + 44}{107 + 44 + 6 + 3} = 0.9438 \approx 94.38\%$$

$$Recall = \frac{107}{107 + 3} = 0.9727 \approx 97.27\%$$

$$Precision = \frac{107}{107 + 6} = 0.9469 \approx 94.69\%$$

$$f1\ Score = 2 \times \frac{0.9469 \times 0.9727}{0.9469 + 0.9727} = 0.9596 \approx 95.96\%$$

From CNN algorithm's confusion matrix,

$$Accuracy = \frac{104 + 12}{104 + 12 + 38 + 6} = 0.725 \approx 72.5\%$$

$$Recall = \frac{104}{104 + 6} = 0.9455 \approx 94.55\%$$

$$Precision = \frac{104}{104 + 38} = 0.7324 \approx 73.24\%$$

$$f1\ Score = 2 \times \frac{0.7324 \times 0.9455}{0.7324 + 0.9455} = 0.8254 \approx 82.54\%$$

From VGG16 algorithm's confusion matrix,

$$Accuracy = \frac{110 + 0}{110 + 0 + 50 + 0} = 0.6875 \approx 68.75\%$$

$$Recall = \frac{110}{110 + 0} = 1.0 \approx 100\%$$

$$Precision = \frac{110}{110 + 50} = 0.6875 \approx 68.75\%$$

$$f1\ Score = 2 \times \frac{0.6875 \times 1.0}{0.6875 + 1.0} = 0.8148 \approx 81.48\%$$

From MLPs algorithm's confusion matrix,

$$Accuracy = \frac{124 + 0}{124 + 0 + 36 + 0} = 0.775 \approx 77.5\%$$

$$Recall = \frac{124}{124 + 0} = 1.0 \approx 100\%$$

$$Precision = \frac{124}{124 + 36} = 0.775 \approx 77.5\%$$

$$f1\ Score = 2 \times \frac{0.775 \times 1.0}{0.775 + 1.0} = 0.8732 \approx 87.32\%$$

5.2 Dataset Description

We have used a total of 800 images data for predicting the “Disease Affected Eggplant” and also “Fresh Eggplant” where 560 images are for training means 70% of eggplant images are for training dataset, 80 images means 10% of total eggplants are for validation, and 160 images means 20% of images are for testing. We have taken two types of disease for detecting the eggplant disease or not and the two types of attributes are “leaf blight” and “fruit rot diseases”. We have collected our model dataset from the various link as shutterstock.com, plantvillage.psu.edu and garden.org and also collected using online serve. We have stored our eggplant dataset in our own GitHub link (<https://github.com/imdadulhaque1/eggplant>).

CHAPTER 5

Experimental results and discussions

This is mainly deep learning-based research project where we have used mobileNet, CNN, VGG16 and MLPs and all the deep learning algorithms performs on our own eggplant dataset to predict eggplant rot disease and also leaf disease. Our research-based project also known as comparison project and we have get the four different accuracy from the different deep learning algorithms. We used 100 epochs for training our model to predict the disease of eggplant as rot disease and leaf disease or it will be providing as the fresh eggplant (flowchart).

Table-2: Accuracy

Algorithm Name	Training (last accuracy)	Validation (last accuracy)	Test / Overall accuracy
mobileNet	97.50%	100%	95.63%
CNN	97.50%	85.00%	81.88%
VGG16	75.00%	75.00%	70.63%
MPLs	66.72%	64.42%	77.50%

From the table-2, the last epochs as 100th epochs provide the training, validation accuracy for mobileNet are 97.50%, 100%, for CNN are 97.50%, 85.00% for VGG16's training and validation accuracy are 75.00%, 75.00% and for MLPs (Multi-Layer Perception) training and validation accuracy are 66.72%, 64.42. Now the overall accuracy of the model is also known as test accuracy for mobileNet is 95.63% accuracy which is the best and performs better than others algorithm and for CNN, VGG16, MLPs accuracy are 81.88%, 70.63%, 77.50%. So, it is proved that mobileNet as Transfer Learning performs better and it the farmers use transfer learning based mobileNet algorithm performs more accurately. With the pretty accuracy transfer learning as mobileNet is also so fast model with the less loss and higher validation and training accuracy.



Figure 13: Experimental images.

CHAPTER 6

Conclusion

6.1 Limitations

Though we have done a good job on our research, it has some limitations. We collect our datasets from [shutterstock.com](https://www.shutterstock.com). That's why the logo and trademark of this page are included in all the images we have collected. For this reason, the quality of accuracy has been a bit of a hassle. So, with a better dataset we can gain more than our obtained accuracies. We will fulfill our limitations to do a better job in future.

6.2 Future Scope

Within the extension and limitation of our work, the future scope of our work will be very unprecedented. We will do the detection on petals also. We will do some work that will detect the diseases individually. And we will implement a software basis operator on our model that will detect eggplant disease effortlessly, and it'll help the poor farmers to diagnose their crops accurately.

6.3 Conclusion

In this eggplant disease detection research, we have work in Transfer Learning with MobileNet, CNN, Multilayer Perceptron & VGG16 method to detect the eggplant leaf and fruit disease. MobileNet did a great job to detect the disease of eggplant between affected and non-affected eggplants. It gives testing accuracy 95% that is probably better than other methods. Other methods (CNN, Multilayer Perceptron & VGG 16) that we had worked with also did a great job to detect the diseases, but MobileNet is the best all of them.

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