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DETECTION OF PLANT DISEASE USING DEEP LEARNING TECHNIQUES

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ABSTRACT

Deep Learning(DL) is one of the parts of machine learning methods based on artificial intelligence network with the representation of learning. Deep learning techniques help to process and analyze big data available around us through several applications in various fields related to the subject. The concept of plant disease is the scientific study of plants where the disease in plants is caused by pathogens and other environmental conditions. In order to identify the disease and curing them in the initial stage is the better option. Automatic and perfect identification of plant disease is important in the aspects of food security, managing disease, and predicting it. DL method helps in detecting the disease's severe-ness. With the leaf of apple plant with rot images in the Plant-Village dataset are explained by botanists with 4 stages of severe-ness. The deep learning convolutional neural network are trained for analysing the severe-ness in the plant disease.

This research tries to analyze the transfer learning method with the help of a deep model and trained networks from scratch. The deep VGG16 model under the training of transfer learning was found to have an accuracy of 90 percent on the test. The DL method will have a huge significance in disease control in plants in the field of modern agriculture.

Key words: Deep Learning (DL), plant disease, food security, managing disease.

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1. INTRODUCTION

According to today's technology and advancement in resources, human beings can produce the quantity of food needed for the entire population worldwide. But the concept of food security is under threat due to various factors like climate change, a decrease in pollinators, several other diseases in plants, etc.

Plant disease may not only be considered as a serious warning in the aspect of food security on the world level, but they are a serious threat for small scale farmers who deepen on farming and agriculture. According to the United Nations Environment Programme of 2013, the loss in yield was found to more than 50 percent because of pests. Almost 50 percent of people in Hungry depend on small scale farming, those farmers are at risk of pathogen based interruption in the food supply.

[38] Efforts have been to prevent plant loss because of these kinds of plant diseases. The Integrated Pest Management Method is the practice of suppressing the pest population below the economic injury level. The IPM can be used for agricultural as well as non-agricultural purposes like house gardens etc. It helps in detecting the disease in the plant in the beginning stage which is the most important step in management. In the historic times the identification of plant disease was done by the agricultural organization, and other plant clinics, etc. but in recent times it is also done online by giving information about the plant disease. The tools in our mobile phone have increased quite well in numbers to detect the disease in the plant. Mobile phone tools have taken place worldwide.Smartphones are very helpful for detecting diseases in the plants because of special features like computing power, providing HD displays, and also giving access to HD cameras for capturing high-quality images of the plants. In a recent report, it is found that nearly 5-6 B smartphones will be in 2020 worldwide. By the end of 2015, it was found that almost 69 percent of people have access to mobile broadband, in 2015 itself it reached up to 47 percent, it has increased in a larger amount when compared to 2007.

The reason for more people utilizing smartphone because of High Definition Camera, and high processors in smartphones made detecting of plant disease diagnosis through recognition of images of plants. It can be feasible if technology reaches a wider population. Technology feasibility is illustrated using DL method by capturing 54,300 images from 14 species of crops with almost 26 type of plant disease and made it available in Plant-Village. This is shown in fig 1 as follows.

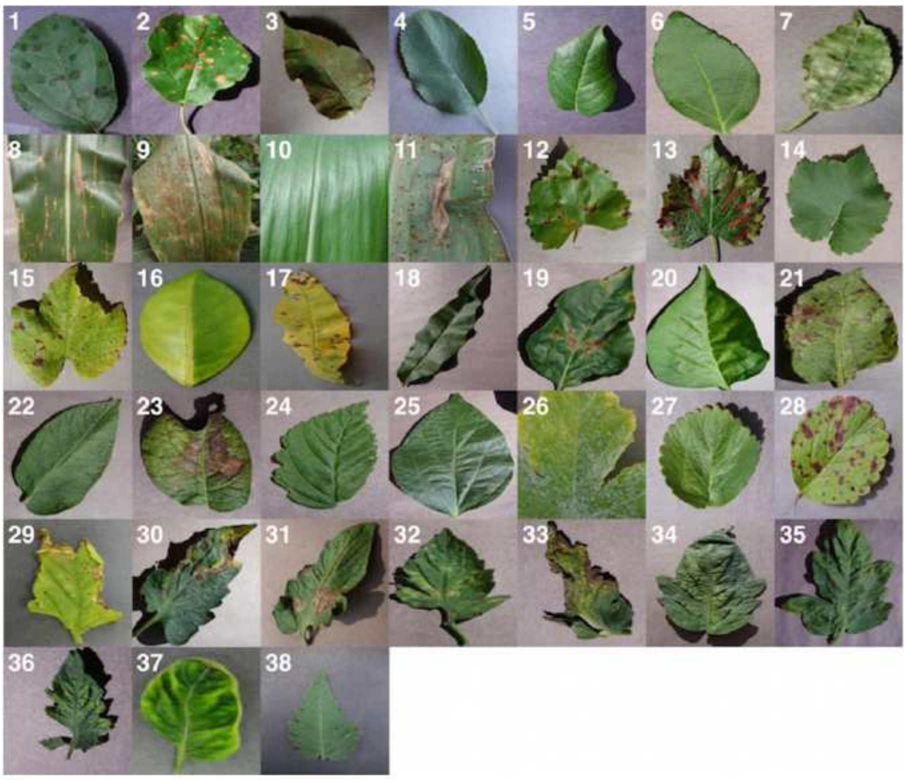


Figure 1 Example of leaf images from the Plant-Village dataset, representing every crop-disease pair used.

Table 1

Numbering of Plants	Plant Name	Botanical Name
1	Apple Scab	Venturia inaequalis
2	Apple Black Rot	Botryosphaeria obtusa
3	Apple Cedar Rust	Gymnosporangium juniperi-virginianae
4	Apple healthy	-
5	Blueberry healthy	-
6	Cherry healthy	-
7	Cherry Powdery Mildew	Podoshaera clandestine
8	Corn Gray Leaf Spot	Cercospora zeae-maydis
9	Corn Common Rust	Puccinia sorghi
10	Corn healthy	-
11	Corn Northern Leaf Blight	Exserohilum turcicum
12	Grape Black Rot	Guignardia bidwellii
13	Grape Black Measles (Esca)	Phaeomoniella aleophilum, Phaeomoniella chlamydospora
14	Grape Healthy	-
15	Grape Leaf Blight	Pseudocercospora vitis
16	Orange Huanglongbing (Citrus Greening)	Candidatus Liberibacter spp
17	Peach Bacterial Spot	Xanthomonas campestris
18	Peach healthy	-
19	Bell Pepper Bacterial Spot	Xanthomonas campestris
20	Bell Pepper healthy	-
21	Potato Early Blight	Alternaria solani
22	Potato healthy	-
23	Potato Late Blight	Phytophthora infestans
24	Raspberry healthy	-
25	Soybean healthy	-
26	Squash Powdery Mildew	Erysiphe cichoracearum
27	Strawberry Healthy	-
28	Strawberry Leaf Scorch	Diplocarpon earlianum
29	Tomato Bacterial Spot	Xanthomonas campestris pv. vesicatoria
30	Tomato Early Blight	Alternaria solani
31	Tomato Late Blight	Phytophthora infestans

32	Tomato Leaf Mold	Passalora fulva
33	Tomato Septoria Leaf Spot	Septoria lycopersici
34	Tomato Two Spotted Spider Mite	Tetranychus urticae
35	Tomato Target Spot	Corynespora cassiicola
36	Tomato Mosaic Virus	-
37	Tomato Yellow Leaf Curl Virus	-
38	Tomato healthy	-

[39] [16]The PASCAL VOC and ILSVRC on the idea of ImageNet data are used as a notable concept of many visualization concepts in computer network it also includes classification of an object.

[25] [27] In the year 2012, a deep conventional network achieved an error of 16 percent under the classification of images into a thousand possible categories. But in the following years, the deep conventional network tried to reduce the error to 3.5 percent. Training of neural networks may take quite a considerable time, but already trained networks can categorize images very quickly, by which they can be suitable for consumer apps in smartphones.

[32] The concept of neural networks has been implemented in many fields including END-to-END learning. These neural networks give mapping connecting inputs – the image of the diseased plant, via the output – a pair of an image of crop and its disease. The nodes in this network are mathematical that take numerical inputs of income edge and gives a numerical output of outcome edge. A deep neural network is just the concept of mapping the inputs and the outputs over a series of nodes. The main challenge of this deep neural network is to have a complete structure of this network, functions, and edges where the input and output must be mapped correctly. The mapping of this network is improved during the process of mapping by giving training to the parameters. The concept of the neural network has improved in the aspects of its concept and engineering breakthroughs.

To get accurate image for detecting the disease in plant a large dataset of images where the plants affected by disease as well plant in normal condition is needed. But these kind of dataset was not available and in fact these kind of dataset don't even exist in the past.

[40] Proposed a framework on disease identification in pomegranate which worked on the basis of segmentation of disease detected area, color, and texture of the infected pomegranate are used as feature. Neutral network was used for classifying the disease. The accuracy of categorisation is found to be 97 percent in this model. This model faced disadvantage because only limited crop was taken as sample.

[2] Proposed a framework onidentifying disease in the cotton leaf, snake segmentation is implemented in this method. The accuracy of the classification is founded as 85 percent.

[3] Proposed a framework identifying the leaf disease and grading is done through Computer vision. The defeated area is segmented using K-means cluster, gray level co-occurrence matrix is utilized for extracting the features of texture. Disease grading in this model is done using fuzzy logic. The ANN is the classifier which is utilized for checking severe-ness in the diseased leaf.

[4] Proposed a framework for identification of bacteria in banana. In this model Naïve bayes is the classifier.

[5] Proposed a framework for identifying disease in the wheat leaf. The color feature in this model is presented using RGB-HIS through gray level co-occurrence matrix. 7 invariant is

taken for shape parameter. The support vector machine is utilized as the classifier which contains modulation and coding scheme for detection of wheat plant in offline.

2. DEEP LEARNING PROPOSAL

2.1 Deep Convolutional Neural Network

In order to know more about neural network for the plant disease and its severe-ness can be identified by training dataset, for this purpose 2 model were compared building a network from scratch and transfer learning.

The shallow networks contains few number of layers with filters in every layer, followed by 2 fully connected layers, with softmax in the end. The training for network 2-10 layers. Each layer has 32 filters with 3 × 3 size, Rectified Linear unit activated and the layers are followed by 2 × 2 size of max-pooling layer, exception from the last convolutional layers with 64 filters in it. The 1st fully connected layer contains of 64 unit of Rectified Linear unit which is followed by the dropout layer, the ratio of dropout layer is 50 percent. In the case of last fully connected layer which contains four outputs, four class, feed to the softmax for the calculation of output.

2.2 Transfer Learning

Only limited amount of image can be learned. Transfer learning is very helpful in building a strong classification network through data, ImageNet. The plant disease severeness classification is chosen for finely grained image classification compared with the ImageNet. The 1st layer displays the direction and color. Fig 2 illustrates the VGG16 model. Even though this model was not trained for plant disease, but it can be operated for spots of the disease, leaves and the background of the plant.

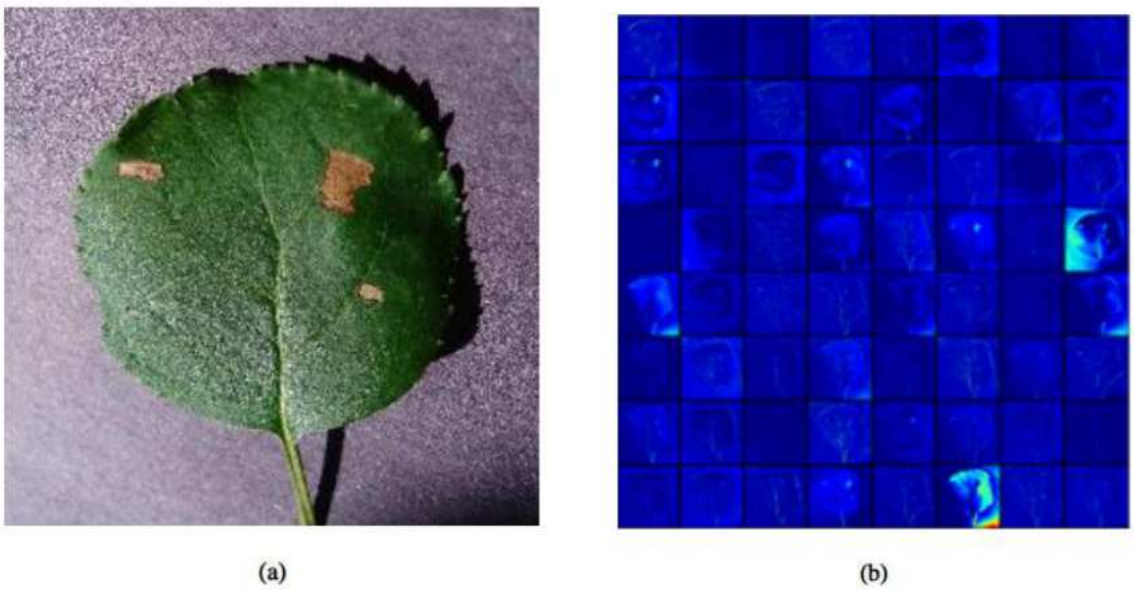


Figure 2 Visualization of activations for an input image in the first convolutional layer of the pretrained VGG16 model: (a) original image; (b) the first convolutional layer output.

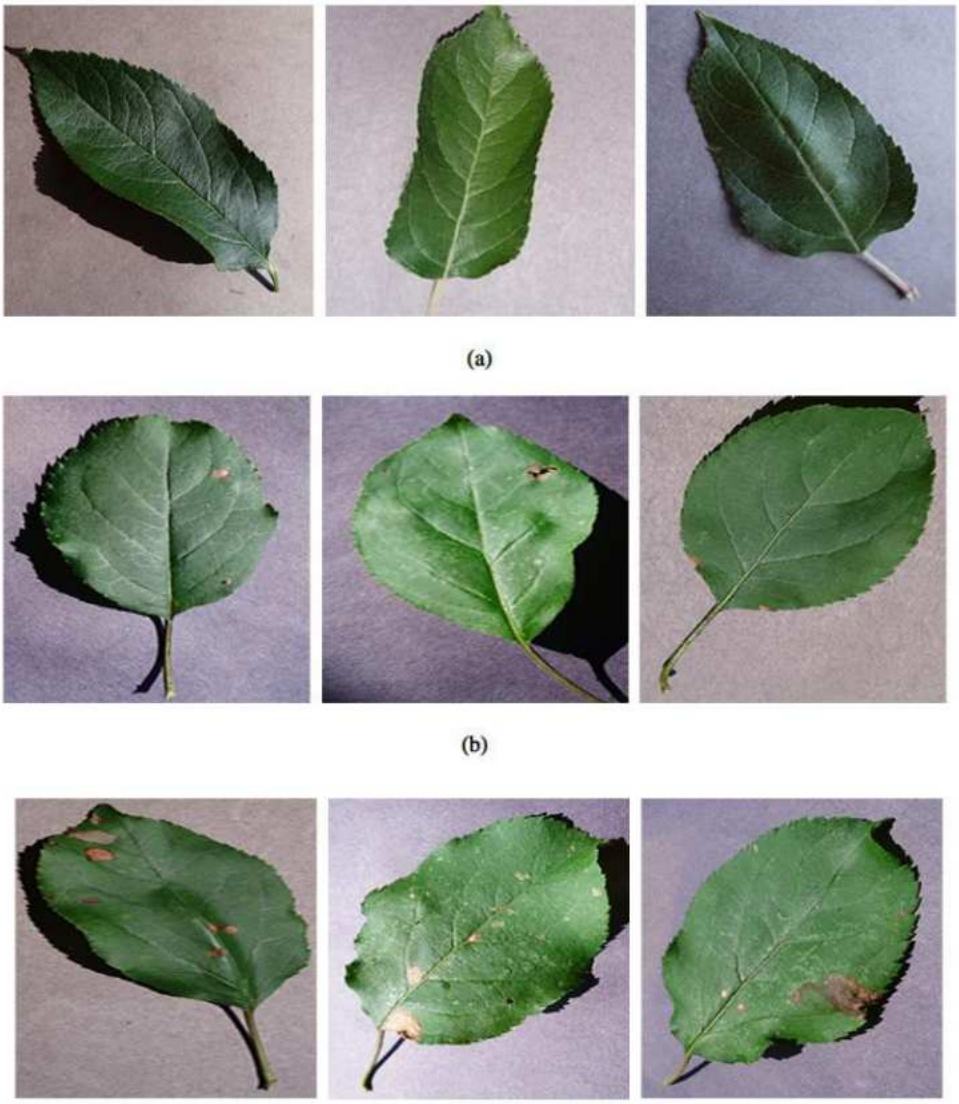
For the concept of TL comparison was made between VGGNet, Inception-v3, and Residual Neural Network50. The VGGNet and the Inception model gives the same performance in 2014 ImageNet ILSVRC. In 2016 ResNet was the winner of challenge. The VGGNet includes 16 and 19(VGG16, VGG19) they showed better improvement by usage of small convolution filters.

3. MATERIAL AND EXPERIMENT

3.1 Data Material

The Plant-Village is a database that contains 50 thousand images of plants in normal condition as well as plants infected with disease, which are categorized under 38 classes. The image of apple leaves and the apple leaf with black rot which is caused through fungus is selected. The images are categorized into different class by the botanists as healthy, early, middle and end stages.

In the healthy stage, leaves have no spots on it. In the early stage, leaves had some spots with is very small. The spots were in 5 mm in the early stage. In the middle stage, the leaves had many spots than the early. The size of the spot was bigger in this stage. But in the end stage, the entire leaves were filled with spots and it looked like that the leaf will fall from the tree. The spots in the leaves were examined and analyzed by agricultural experts and they were labelled with a perfect level of disease severe-ness. Nearly 179 images of plants were abandoned by the experts. Fig 3 illustrates the image of the plants in all stage. As a results healthy stage – 1640 image, Early stage – 130 image, Middle stage – 175 image, End stage – 120 image.



(d)

Figure 3 Sample leaf images of the four stages of apple black rot: (a) healthy stage, (b) early stage, (c) middle stage, and (d) end stage

In the result it is found that the healthy was much than that of the infected one. There is a huge difference in the samples per class. The number of samples should have stability in order to avoid bias in network. The strategy for stability followed in this research includes 80 percent of images from early, middle and end stages were used for training, and the remaining 20 percent are utilized for test set. In the healthy stage the images were divided into 12 groups, with 115 image in each group for training, 25 images were used for testing. 12 runs of groups were used for estimating the accuracy. The Plant-Village contains images of same leaf captured at different angle. The captured image should be under training or testing sets. The images used for training and testing is tabulated in 1.

Table 2 The number of samples in training and test sets

Class	Number of images for training	Number of image for testing
Healthy stage	110 x 12	27 x 12
Early stage	108	29
Middle Stage	144	36
End Stage	102	23

3.2 Image Preprocessing

The sample of Plant-Village data are images with random size of RGB. The image pre-processing is done under following stages: the images are resized for shallow network of size 256 × 256, for VGG16&19, and Residual Neural Network50 the images are resized into 224 × 224, and for Inception- V3 images are resized into 299 × 299. The optimization and prediction for the resized images are done. The value of the pixels are divided by 255 to be compatible in the initial value. Normalization is doe sample wise. The normalization is performed on the basis of each input, the mean value is calculated, then the STD is also arrived by transforming the input to $X'=(x-m_x)/s_x$.

3.3 Neural Network Training Algorithm

A convolutional layer acts as a fully connected layer between the 3-D input and the output. The input is considered as the window of pixels with channels of depth in it. A kernel is a matrix with a slid across the image which is multiplied with the input so that the output is enhanced in a desired manner. The kernel size convolutional layer is

$$x_{ic} = \mathrm{ReLU}\left(W_i * x\right), \tag{1}$$

Where, *- operation of convolution, Wi- layers of convolution of kernel, k- no. of convolution kernel. ReLU- Retified Linear Function.

Max Pooling is a convolution process where the kernel extracts more value of the area convolves. Pooling layer is advisable for reducing the number of extracted features and to avoid over fitting.

The loss is measured between the result predicted and the label of input which is shown as:

$$E(W) = -\frac{1}{n}\sum_{x_i=1}^{n}\sum_{k=1}^{K}\left[y_{ik}\log P(x_i = k) + (1 - y_{ik})\log(1 - P(x_i = k))\right], \quad (2)$$

W-Weight Matrix, n-no.of samples used for training, i- training sample index k-class index.

The training of the samples aims to find out the factor that is responsible for minimizing the loss function. The gradient descent algorithm is used:

$$W_k = W_{k-1} - \alpha\frac{\partial E(W)}{\partial W}, \quad (3)$$

In this algorithm the learning rate must be carefully analysed because it is the important factor which involved in determining the size of the learning.

Early stoppage for stopping the training is used when the network tries to overfit with data. The performance of the network can be obtained at the end of epoch using testing set. The network will stop training if the test is not improving in its performance.

In order to protect the network from overfitting the TL is conducted through: the layers that are fully connected are replaced with the newer one. The replacement is done using the top convolutional layer of VGG16&19, the top inception-v3, ResNet50 along with the new layer.

The new connected layer should be started with perfect values rather than giving values to them randomly. Now except the new layer all the other layers are freezed. The new layer is trained for the output of the end convolutional layer.

The top convolutional layer of VGG16&19, the top inception-v3, ResNet50 are not freezed to train them along with the new layer with less learning rate.

The hyper-parameters of training is tabulated in 2. The learning rate schedule is included. In the initial stage the learning rate is lowered by ten factor of fifty epochs, in the concept of training shallow networks with convolutional layer lesser than 6.

In the learning rate the 10 factor of 100 epochs of shallow network with convolutional network is within or more than 6. The network needs more training for coverage.

Table 3 The hyperparameters of training

Transfer Learning			
Parameters	**Learning from scratch**	**Training fully connected layer**	**Fine Tuning**
Training Algorithm	SGD	RMSP	SGD
Learning rate	0.01	0.01	0.0001
Batch size	32		
Early Stopping	10 epochs		

3.4 Implementation

The experiment is performed on an Ubuntu workstation equipped with one Intel Core i5 6500 CPU (16 GB RAM), accelerated by one GeForce GTX TITAN X GPU (12 GB memory). The model implementation is powered by the Keras deep learning framework with the Theano backend

4. RESULT AND DISCUSSION

Fig 4 illustrates the shallow networks training and testing process. In this bar chart each bar is the result of 12 runs. The accuracy of the training and testing is improved slightly in the beginning of the model. The model's best performance is considered where the accuracy of the test is 79 percent which is achieved through eight layer of convolution. The accuracy of the test may fall when the depth of the network exceeds more than 8. In order to overcome this problem the TL is applied based on the state-of-the-art model.

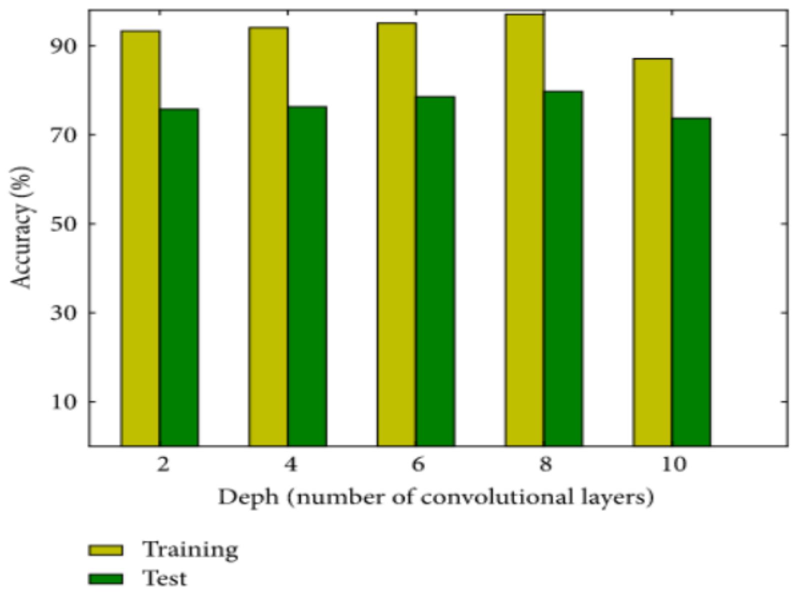


Figure 4 Accuracies of shallow networks

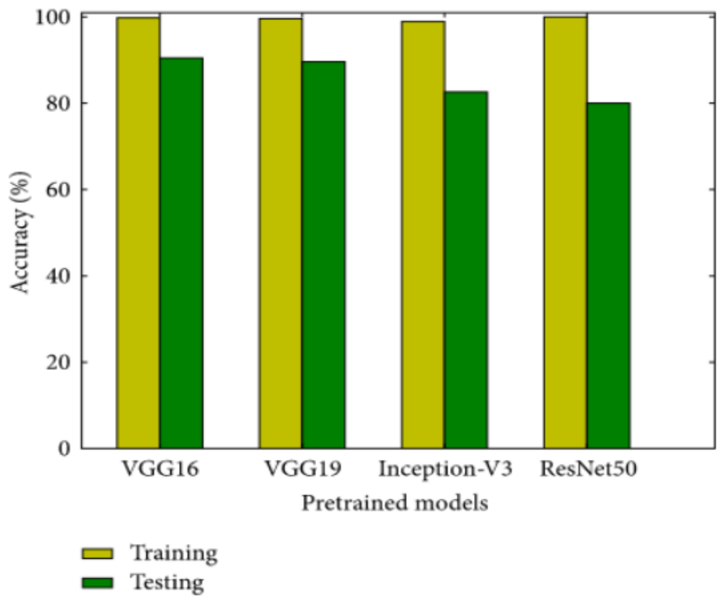


Figure 5 Accuracies of the state-of-the-art extreme deep models trained with transfer learning

Fig 5 illustrates the fine tuning of the ImageNet model. In this bar chart each bar is the result of 12 runs. The accuracy of the test result obtained varies. This model is superior when compared to the model trained using scratch. The result of VGG16 is considered to be the best one. With 90 percent accuracy. The result shows that the training in transfer learning method is insufficient.

The Artificial Neural Network is trained using Stochastic Gradient Descent on the training set. The accuracy in the test result is obtained as 30 percent. The result is guessed on random basis. The Artificial Neural Network cannot extract local correlation without convolutional feature extractor. The discriminative features cannot be learned from the image.

Table 3 illustrates the confusion matrix of VGG16 model. The accurately predicted images are explained in detail in the tabulation. The classification is correctly done with the health-stage leaves. The accuracy of the early stage is 92 percent and the end stage is 85 percent. The middle stage of the leaf was not classified properly. The accuracy of middle stage is 80 percent. The stage which is not classified properly led to confusion among the other stages.

Table 4 Confusion matrix for the prediction of VGG16 model trained with transfer learning.

Predicted					
		Healthy stage	**Early stage**	**Middle stage**	**End stage**
Ground truth	Healthy stage	27	0	0	0
	Early stage	0	27	2	0
	Middle stage	0	5	30	1
	End stage	0	0	3	20

The result is illustrated in fig 5 it is found that the accuracy of deep learning is almost nearer to 100 percent. The training of data can increase the accuracy of the test result. The test best performance is achieved through the VGGNet model. The performance of VGGNet is better in plant identification task the PlantCLEF. When comparing the performance of VGGNet the performance of ResNet is considered to be poorer on fine-grained classification. The Stochastic Gradient Descent optimizer may put residual mapping in ResNet. This may lead to local optimization and poorer generalization.

5. CONCLUSION

This research proposed a framework of deep learning in order to identify the disease and curing them in the initial stage is the better option. Automatic and perfect identification of plant disease is important in the aspects of food security, managing disease, and predicting it. DL method helps in detecting the disease's severe-ness.

The training in this research is conducted on the base of small convolutional networks with various depth from scratch and finely-tuned 4 stage of state-of-the-art model such as VGG16, VGG19, ResNet50, and Inception-v3. When comparing the data obtained from the deep model the performance of the network can be improved in certain dataset. The result showed that the VGG16 is considered to be the best one. With 90 percent accuracy. Which shows deep learning is new approach in the aspect of identifying plant disease and classifying them based on the severe-ness of the disease.

In the further study the data of various levels and different type of plant disease should be collected using adaptable sensors. The deep learning can be used for recommending treatment for plant disease and many more.

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