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# A Comparative Analysis on Deep Learning Models Applied for Disease Classification in Bell Pepper

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**Abstract**

Agriculture is the mother of all civilizations. The focus is on improving productivity without taking into consideration the environmental effects that have appeared in the degeneration of the environment. Plant diseases are very important as this can especially imply both the quality and quantity of plant in the development of agriculture. Generally, the diseases of plants include fungi, bacteria, viruses, moulds, etc. Farmers or specialists typically recognize plants disease and diagnosis them with naked-eyed. Crop diseases are one of the leading causes of agricultural product quality degradation and reduction. As a result, early detection of the condition is extremely important .We were inspired by the ability of deep learning approaches to match patterns and interpret images to create an automated disease detection tool for bell pepper plants. The various applications of deep learning models supports comparative study for categorization of plant diseases. The applied deep learning models namely VGG16, MobileNet, and ResNet50 were applied on a publically available dataset of the bell pepper plant. Here we trained the data set with above three transfer learning algorithms. After that the output layer of these algorithm passed through the convolutional neural network layer. The experimental results shows that ResNet50 model will give the better accuracy and least amount of training time than other models.

**Keywords—Deep learning, Convolutional Neural Networks, Plant disease**.

## I. INTRODUCTION

Agriculture is the primary need for meeting the world's food requirements. The main reasons for the gap in agricultural product demand and supply are an increase in population and a decrease in agricultural land. Plant diseases are also to blame for crop quality degradation and yield reduction. Traditional agricultural practices do not ensure the quality of crop products. These practices are deficient in disease detection. In addition, these practices necessitate the use of human experts to detect pathology in plants. As a result, there is an urgent need for time to invent and implement technological solutions for early diagnosis of plant diseases.

This paper make good use of deep learning algorithm image processing capabilities for early diagnosis of plant diseases. For the experiments, we choose the Bell Pepper plant. Because this

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| Paper | Year | Classes | Images | CNN models | Crop | Accuracy % |
|---|---|---|---|---|---|---|
| Our work | 2022 | 10 | 4000 | Vgg-16<br>MobileNet<br>ResNet-50 | Bell pepper | 97.49 |
| [4] | 2018 | 38 | 54323 | AlexNet<br>DenseNet-169<br>InceptionV3<br>ResNet-34<br>VGG-13<br>SqueezeNet-1.1 | 14 species | 99.76 |
| [6] | 2017 | 3 | 1918 | VGG16 | Maize | 99.58 |
| [11] | 2018 | 4 | 14,208 | AlexNet | Cucumber | 93.4 |
| [12] | 2019 | 8 | 2430 | VGG<br>InceptionV3<br>ResNetDenseNet | Cucumber<br>Rice | 97.14 |
| [15] | 2019 | 32<br>15<br>40<br>38 | 1907<br>1125<br>443<br>54,306 | Endto end CNN<br>Fine tuning<br>CNN-RNN | Flavia leaf Swedish leaf UCI Plant village | 97.40 |
| [16] | 2018 | 2 | 1100 | VGG-19 | Sugar beet | 98.4 |

**TABLE 1. Related Summery of Plant disease classifier**

plant are high demand around the world in salads, cooked vegetables, and other cuisines. In addition, the bell pepper is a low-calorie food with high nutritional value [1]. However, microbial attack has severely harmed the product's quality. Fusarium wilt, Bacterial Leaf Spot (BLS), powdery mildew, anthracnose, blossom end rot, and leaf and fruit blight are among the diseases that can easily infect it [2].

This study used a dataset [Plant village] including photos of bell pepper leaves to conduct an empirical analysis of deep learning models. Deep Learning (DL) offers a fresh approach to illness detection and categorization automation [3][4]. The authors of [5] argued that DL approaches perform better in automatic disease diagnosis and classification than traditional and machine learning techniques. Convolutional Neural Networks (CNN) are a type of deep learning approach that can be used for image classification, recognition, and object detection, according to the authors in [6][7].CNNs are sophisticated algorithms that take photographs of plant leaves as input, evaluate them, and categories them as healthy or unhealthy .

## II. RELATED WORKS

The authors did a thorough evaluation of comparable research in the field of plant disease detection and categorization. They discovered that numerous approaches for detecting and identifying plant diseases have been discussed by researchers. The use of computer vision in the identification of plant disease was favored by the researchers [10]. The author of [4] used different training methods to compare six deep learning models, namely AlexNet , DenseNet-169, Inception v3, ResNet-34, SqueezeNet-1.1, and VGG13, on the Plant Village dataset [54,306 images, 14 crop species, and 26 diseases with 38 class labels]. On the training and testing datasets, they reported that Inception v3 and DenseNet169 accuracy is equivalent. Dense Net recorded the best accuracy of 99.76 percent, whereas Inception v3 achieved the maximum accuracy of 99.72 percent. They also stated that DenseNet took less time to train than the Inception v3 model.

The size of the model and the size of the training data are interdependent. If the CNN model is not modified according to the amount of the dataset, it may experience overfitting and under fitting issues. In order to achieve the effectiveness in categorizing the testing dataset, a CNN-based model must be trained with a small dataset. As a result, data augmentation techniques such as rotation, shear, flipping, and zoom are required [11][12]. In [13][14], the authors used augmentation techniques like geometric transformations, color space augmentations, kernel filters, picture mixing, random erasing, and feature space augmentation to improve the model's results. The authors of [6] used enhancement techniques on photographs of flora from 1918. They raised the number of photos in the collection to 4588.Another method for making exact predictions with a minimal dataset for training the CNN model is Transfer Learning [12][15]. The initial layers of the CNN model are trained with photos from any dataset in this method. This aids the network's learning of basic properties like image object detection and border detection. The training of the network's early layers is now prohibited. The last three pooling and convolution layers, as well as the dense layers, are trained on the unique dataset. This is useful for teaching the models about the high-level properties of the images, such as shape and size. As an example, the CNN model is trained on a dataset of potato plant leaves.

This is important for teaching models about high-level properties like the form and size of a certain object. As an example, the CNN model is trained using the dataset of potato plant leaves to familiarize it with the detection of boundaries Later on, this CNN reporter who had been pre-trained Images of healthy and unwell people are used to train the model. The leaves of the bell pepper this aids the network's understanding of the differences between sick and healthy .

Bell leaves despite the fact that the dataset is small the switch was made. Learning can also be used to fine-tune the hyper parameters of a system. Transfer learning can also be used to fine-tune the CNN model's hyper parameters based on the dataset. Transfer learning is also beneficial for fine-tuning the CNN model's hyper parameters based on the dataset. The project demonstrates the significance of the transfer learning [16]. The writers conducted a comparative investigation in this paper. AlexNet, VGG-19, GoogLeNet, and other deep learning models ResNet-50, ResNet-101, and Inception-v3 are three different types of neural networks. They applied these models on the images of sugar beet plants [1100] images manually extracted at Uniform experimental sites in

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[Wageningen]. They reported that the model .VGG-19 outperforms the other models with an accuracy of 98.7%. The detailed summarization of some studies is given in Table I.

## III.MATERIALS AND METHODS

This section presents the details about the dataset collection, training and testing of the CNN models pertained on the publicly available dataset Plant village[17]. It employs the techniques of transfer learning[15] for the feature extraction and basic CNN layers are used to classification. The main purpose of proposed system is to detect the diseases of plant leaves by using feature extraction methods where features such as shape, color, and texture are taken into consideration. Convolutional neural network (CNN) and transfer learning methods (Resnet,Mobilenet,Vgg16), a machine Algorithm classifying the plant leaves into healthy or diseased and if it is a diseased plant leaf, CNN will give the name of that particular disease. Suggesting remedies for particular disease is made which will help in growing healthy plants and improve the productivity. First the images of various leaves are acquired using high resolution camera so as to get the better results & efficiency. Then image processing techniques are applied to these images to extract useful features which will be required for further analysis.

## METHODOLOGY

The model block diagram as shown in Figure:1 As clearly seen from the figure , the model consist of three main stages: data preprocessing, deep learning models for feature extraction ,and classification. The proposed model uses bell pepper plant leaf images as inputs, and the final output is the classification of the input image in to one of the ten classes, that isBacterial_spot,Early_blight,Late_blight,Leaf_Mold,mosaic_virus,Septoria_leaf_spot,Target_Spot ,Two-spotted_spider_mite,Yellow_Leaf_Curl_Virus and Healthy . The first stage handles image pre-processing, such as resizing, image augmentation, and data, splitting randomly into two groups: training and validation by 80 and 20 percentage, respectively. The dataset images are randomly split into two parts (train and validation) to insure the variety of the images. Data normalization is also used after converting the image to an array of pixels to rescale the image’s pixel value to the interval. The second and third stages are feature extraction and image classification, respectively, by using different types of deep learning approaches.

The deep learning models consist of input, hidden and output layers. The hidden layers include the convolutional, pooling and fully connected layers. The fully connected layers employ the activation function such as ReLu [Rectified Linear Unit].

### A. Dataset :

Plant Village (PV)[18] is a popular dataset collected for evaluation of automatic plant disease identification systems. It contains healthy and infected leaves isolated on a uniform background. In this research work, the authors trained the deep learning models using open and freely available plant village dataset of bell pepper.

### B. Experiment setup :

This section gives the details about the general architecture of the deep learning model, training and testing of the pre-trained models on the dataset containing images of healthy and

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diseased bell pepper plants. The deep learning models consist of input, hidden and output layers. The hidden layers include the convolutional, pooling and fully connected layers. The fully connected layers employ the activation function such as ReLu [Rectified Linear Unit].
For conducting the experiments, here used the deep learning framework Tensorflow[20]. Trained their model and It provides 12GB RAM.

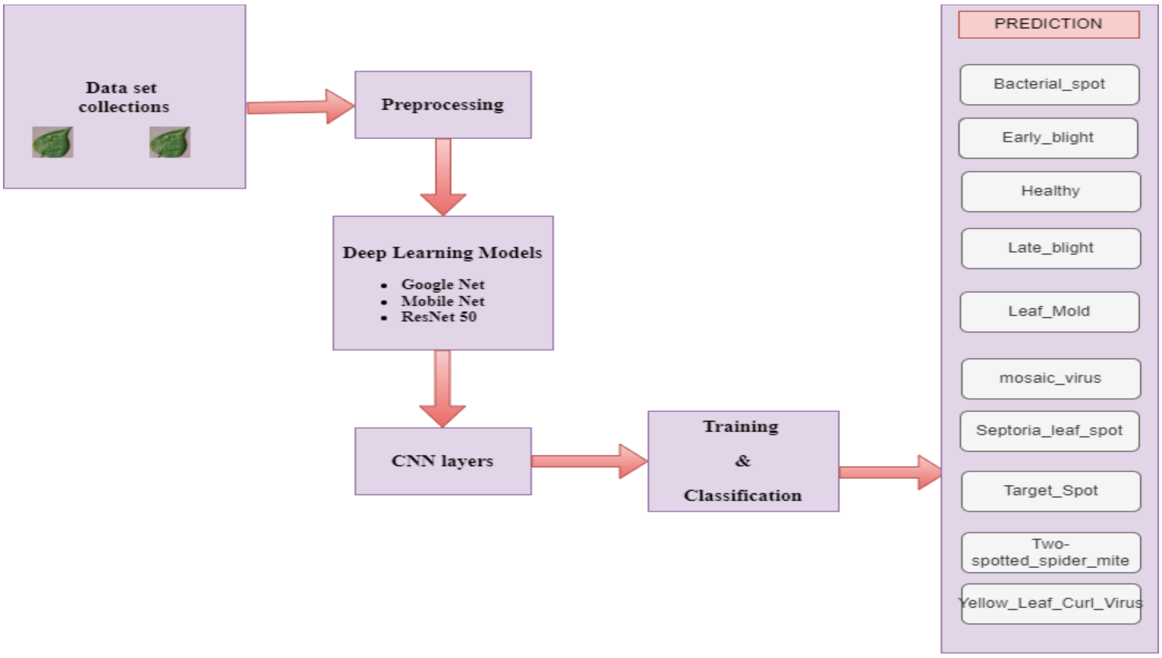


**FIGURE 1.Block diagram of the proposed plant leaf disease classification model**

**Deep Learning Proposed Models:**

In this work, several types of supervised deep learning techniques areutilized for developing the proposed plant leaf disease classification models. Here present the comparative analysis of different deep learning models applied for plant disease classification.Applied the deep learning models namely Google Net(vgg16), MobileNet, and ResNet50 on the publicly available dataset of the bell pepper plant.

VGG16 is object detection and classification algorithm which is able to classify 1000 images of 1000 different categories with 92.7 accuracy. It is one of the popular algorithms for image classification and is easy to use with transfer learning.VGG16 is a variant of VGG model with 16 convolution layers. It is very appealing because of its very uniform Architecture.Similar to Alex Net, it has only 3x3 convolutions, but lots of filters.

MobileNet is a simple but efficient and not very computationally intensive convolutional neural networks for mobile vision applications. MobileNet is widely used in many real-world

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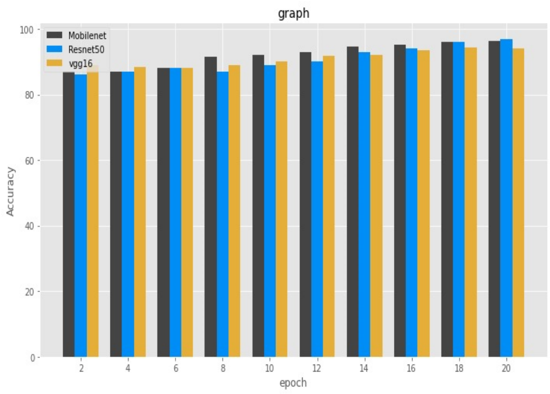
applications which includes object detection, fine-grained classifications, face attributes, and localization.

ResNet, short for Residual Network is a specific type of neural network that was introduced in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun in their paper Deep Residual Learning for Image Recognition.ResNet-50 is a convolutional neural network that is 50 layers deep.The core idea of ResNet is introducing a so-called identity shortcut connection that skips one or more layers.One of the problems ResNet solve is the famous known vanishing gradient. ResNet improves the efficiency of deep neural networks with more neural layers while minimizing the percentage of errors.

## IV.RESULTS AND DISCUSSION

The authors in claimed that VGGNet is the first runner up and outperforms the GoogleNet in ILSVRC-2014 challenge. They claimed that VGGNet with 16 and 19 layers were used with top-5 error rate of 7.3 and 7.5 respectively. This proves that merely increasing the number of layers is not sufficient to reduce the error rate. To address the above stated problem, the authors in proposed the Inception architecture of the GoogleNet. This network reduced the error rate to 3.6 Also, its computational complexity id lowers than the VGGNet model. But, it is difficult to customize this network according to the nature of the problem and the type of the dataset. The evolution in the Residual networks addressed the problem encountered in Inception network. The residual networks make an effective use of the identity blocks or skip connections. Thus, it is easy to train of the models based on the residual networks. These models are optimized to improve the accuracy of prediction. The researchers designed the ResNet model with 50 layers. These models reports the error rate of 3.57 which is lower than the error rate of 7.3 reported by the VGGNet. Thus, the ResNet won the 1st position in the ILSVRC 2015.

The comparison in the performance of the models viz. VGG16, MobileNet and ResNet50 based on the accuracy and loss function demonstrated in graphs shown in Figure 1 to Figure 3. VGG16, ResNet50, and MobileNet models were tested on a publically available dataset of healthy and damaged bell pepper plants.The experimental results shown in Table 2 demonstrate that the ResNet50 performs better than, VGG16 and MobileNet models in terms of accuracy and as well as in execution time.



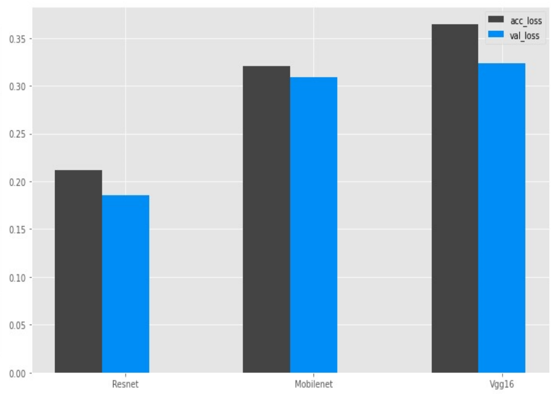




**FIGURE 2.Models accuracy comparison chartFIGURE 3.Models loss comparison chart**

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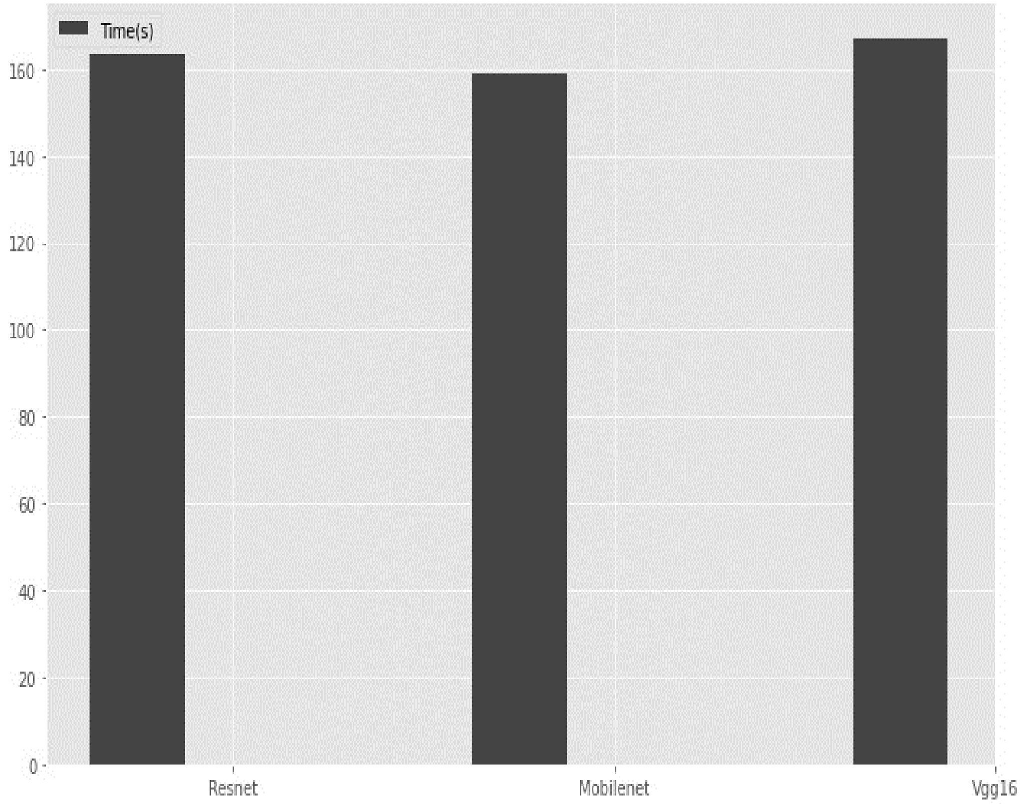


**FIGURE 4.** **Execution time comparison chart**

**TABLE 2.** **Performance Comparison in deep learning Models**

| Model | Training Time(In minutes) Accuracy% | Validation Accuracy% | Training Loss | Validation Loss | Test Accuracy |
|---|---|---|---|---|---|
| VGG16 | 94 | 96.3 | 0.36655 | 0.04245 | 0.9624 |
| MobileNet | 96.2 | 96.8 | 0.31287 | 0.05297 | 0.9671 |
| ResNet50 | 96.7 | 98 | 0.00104 | 0.06655 | 0.9799 |

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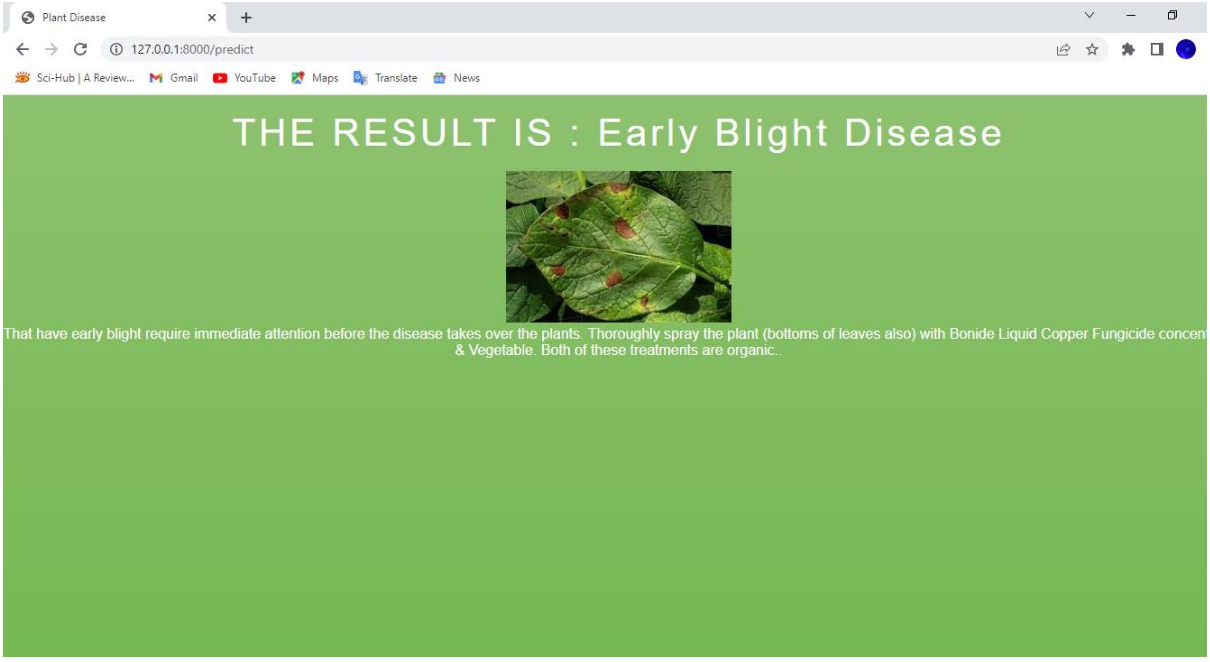


**FIGURE 5.Prediction of leaf image**

## V. CONCLUSION

Given the importance of agriculture and plants in the whole world and in many country, and because of many plant diseases that exist today, this research proposed a robust methodology to detect and classify these diseases with accurate and fast results based on computer facilities and Deep Learning Techniques. To perform the comprehensive review of the deep learning models applied for the detection and classification of plant diseases provided sufficient data is available for training, deep learning techniques are capable of recognizing plant leaf diseases with high accuracy. The leaves of the bell pepper plant are taken as a group of leaves to identify disease. To use multiple techniques and create an expert system that detects and classifies plant leaf diseases. The experimental results shown in Table:2 demonstrate that the ResNet50 performs better than, VGG16 and MobileNet models in terms of accuracy and as well as in execution time. The ResNet50 model achieves the highest validation accuracy of 97.49. This model is the most acceptable for the classification of diseased and healthy crop plants. To Provide sufficient data is available for training, deep learning techniques are capable of recognizing plant leaf diseases with high accuracy. The scope of this work can be implement a fertilizer recommendation system in to this work. Here also get the Leafe disease name so predict the fertilizer names ,that will very helpful to the farmers.

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