Plant disease classification using deep learning

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***Abstract*—Agriculture plays a crucial role in the Indian economy. Early detection of plant diseases is very much essential to prevent crop loss and further spread of diseases. Most plants such as apple, tomato, cherry, grapes show visible symptoms of the disease on the leaf. These visible patterns can be identified to correctly predict the disease and take early actions to prevent it. The conventional method is the farmers or plant pathologists manually observe the plant leaf and identify the type of disease. In this project, a deep learning model is trained to classify the different plant diseases. The convolutional neural network (CNN) model is used due to its massive success in image-based classification. The deep learning model provides faster and more accurate predictions than manual observation of the plant leaf. In this work, the CNN model and pre-trained models such as VGG, ResNet, and DenseNet models are trained using the dataset. Among them, the DenseNet model achieves the highest accuracy.**

Keywords*—Plant disease detection, Convolutional Neural Networks, Transfer Learning, VGG, ResNet, DenseNet.

I. INTRODUCTION

Plant disease detection is a significant challenge in the agriculture sector. Some of the plants show visible symptoms on the plant leaf. These leaf patterns can be used to identify different diseases and take immediate action to prevent the spread. Most of these plant diseases are difficult to detect through naked eyes, and even experienced persons end up wrong. The accuracy of the manual prediction depends upon the experience and knowledge of the person [1]. There are much research works done for plant leaf disease identification using machine learning and deep learning models. This study proposes a deep learning model to classify different plant diseases. In standard machine learning models, the features are extracted manually, and the algorithm learns from that data. Thus it is a two-step process. The deep learning model uses an artificial neural network that can learn features from an input image and make intelligent decisions on its own. Thus deep learning models are far more capable than the standard machine learning models for image-based classification.

The working model uses convolutional neural networks and transfer learning to classify different plant leaf diseases. CNN is a type of deep learning neural network and has good success in image-based classification. The proposed system is faster and more accurate than the conventional way of manual observation of each plant leaf. Deploying such a model into a mobile application can help farmers detect different plant diseases using mobile cameras and take necessary actions to avoid disease spread. For this study, the images of grape plant diseases from the Plant Village dataset are used to train the model. The CNN (Convolutional neural network), VGG19, ResNet-152v2, and DenseNet models are trained using the plant dataset. Among them, the DenseNet model achieved the highest accuracy of 98.27%.

II. RELATED WORKS

In [1] authors proposed a method to classify different plant diseases using the EfficientNet deep learning model. The model was trained using the Plant Village dataset having 55,448 images and the augmented version of the dataset has 61,486 images. The proposed EfficientNet model's performance is compared with other state-of-the-art CNN models such as ResNet, VGG, AlexNet, and Inception model. In transfer learning, all the layers were set to trainable. Among all the models, the EfficientNet B5 and B6 models achieved the highest results.

M. Akila and P. Deepan used Region-based Fully Convolutional Network (R-FCN), Faster Region-based CNN (Faster R-CNN), and Single Shot Multibox Detector (SSD) to classify different plant leaf diseases [2]. The dataset contains plant leaf disease images of commercial crops such as banana, sugarcane, cotton, potato, brinjal, carrot, chilly, rice, wheat, and guava. The images were collected from the internet and by manually taking the photo. The image augmentations such as affine and perspective transformation, rotations, and image intensity transformations were performed to expand the dataset and to prevent the model's overfitting.

In [3], the authors used Caffe deep learning framework with Imagenet weights to classify plant diseases. The model consists of eight learning layers and five convolution and fully connected layers. The dataset was prepared by downloading images from the internet. Image augmentation was performed to increase the dataset and prevent overfitting during the training stage. The proposed Caffe model achieved an accuracy of 96%.

Plant disease detection can be done by targeting the disease-affected places using image processing techniques. Sanjay and Shrikant used simple threshold methods and triangle thresholding methods to segment the leaf and lesion area, respectively [4]. The diseases are classified by calculating the lesion and leaf area. The proposed system achieved an accuracy of 98.60%.

Revathi and Hemalatha used particle swarm optimization (PSO) for feature extraction and Cross Information Gain Deep forward Neural Network to classify different cotton leaf diseases with an overall accuracy of 95% [5]. The color, shape, and texture features are extracted using particle swarm optimization to classify different diseases. The feature extraction method helps to identify the disease leaf spots and increases the model's overall accuracy.

Kulkarni and Patil proposed a methodology for detecting plant leaf diseases using image processing techniques and artificial neural networks (ANN) [6]. The images were filtered and segmented using the Gabor filter. The extracted features that could classify the healthy and diseased samples were used to train the ANN model and achieved an accuracy of 91%.

III. METHODOLOGY OF THE CLASSIFICATION MODEL

The convolutional neural network is used in this work to classify different plant diseases. Fig.1 shows the diagram of the working of the classification model. The first layer in the model is the convolution layer that is used to extract features from an input image. The convolution layer applies different filters on the image to create a feature map and help to extract different features. The convolution layers are followed by pooling layers. The pooling layers reduce the image size and the no of parameters. Common types of pooling operations are max pooling, average pooling, and sum pooling. After convolution and pooling operations, the matrix is flattened into a vector and is passed into the fully connected layer. In this study, rectified linear activation function or ReLU activation function is used for the convolution layer and a Softmax activation function for the output layer. Rectified linear activation function returns the output value if the input is greater than zero and returns zero if the input value is zero or less (1).

$$f(x) = max[0, x] \tag{1}$$

Transfer learning is a method in which pre-trained models are reused for a new task instead of developing models from scratch. These models are trained on a large number of images and can improve the accuracy of prediction. In this study, VGG, DenseNet, and Resnet models are trained using the transfer learning technique. The results of these models are compared with each other, and the performance is analyzed.

The VGG is one of the popular models in ILSVRC 2014. It is made by making improvements on the AlexNet by replacing large kernel filters with multiple filters. The input of the VGG model is 224x224 RGB image. The input image is passed through a stack of convolution layers of 3x3 filters. The convolution layers are followed by 2x2 pixel window Max pooling layers. In this study, the VGG19 model is taken from Keras application with Imagenet weights, and the layers were made non-trainable.

Researchers at Microsoft research in 2015 propose the Resnet model. They have introduced a new architecture called Residual Network. After the AlexNet model, the winner of the ImageNet 2012 competition, all other proposed architecture uses more layers to reduce the error rate. One of the main problems faced is the vanishing/exploding gradient. To solve this problem, the residual network has been introduced. In this architecture, few layers are skipped from training and are connected directly to the output class. It helps to reduce the vanishing/exploding gradient problem.

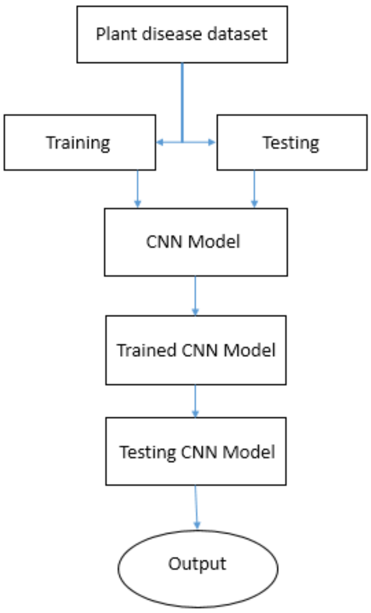


Fig 1. Diagram of the classification system

The DenseNet model is similar to ResNet and is introduced to solve the vanishing gradient problem in large neural networks. The ResNet adds the output of one layer to the next layer, whereas in the DenseNet model, the output feature maps are concatenated with the following future feature maps. The model has different versions such as DenseNet121, DenseNet160, and DenseNet201. The model is divided into different blocks called Dense Blocks, in which the dimensions of the feature maps remain the same and the number of filters changes. Between every dense block, there are transition layers that perform convolution, pooling, and batch normalization. In this study, the DenseNet-201 model with Imagenet weight is used.

IV. IMPLEMENTATION DETAILS

A. Dataset

The data for this study is gathered from the Plant village dataset. The Plant Village dataset consists of more than 55,000 images with 38 classes of 14 different plant species. Out of 38 classes, 12 are healthy, and 26 are diseased leaf classes. In this study, the grape plant leaf images are taken, containing 4,062 images with four classes. The classes are healthy, black rot, Esca (Black Measles), and Leaf blight (Isariopsis Leaf Spot). The dataset consists of 423 healthy leaves, 1,180 black rot affected leaves, 1,383 esca affected leaves, and 1,076 Leaf blight affected images. The sample images from each class are shown in Fig 2-5. Deep learning models require a large dataset to achieve a good performance. Using the Image data generator in Keras, the images are resized into 224x224 pixel size, and augmentations such as rotation, zoom, and shift were applied. The primary purpose of the augmentation process is to expand the dataset and prevent overfitting during the training stage. To perform the experiments, the dataset is split into training and validation set in the ratio of 80:20. The training set contains 3,258 images, and the validation set contains 812 images.

Fig. 2. Healthy grape leaves

Fig. 3. Blight affected leaves

Fig. 4. Black rot affected leaves

Fig. 5. Esca affected leaves

B. *Training Neural Network*

In this study, a convolutional neural network and popular pre-trained models such as VGG, ResNet, and DenseNet are trained using the plant dataset, and results are compared. The CNN model used contains pairs of convolution and pooling layers. The convolution layers perform filters on the input image and extract the features. The pooling layers reduce the size of the input image and reduce the computation performed in the network. Fig 6 shows the schematic representation of the CNN model.

The CNN model is trained using the training set for 20 epochs. The optimizer used is Adam, and the loss function selected is categorical cross-entropy. Adam is an algorithm for stochastic gradient optimization which works well with sparse data. The loss and accuracy plotted during different epochs are shown in Fig 7a and 7b. The CNN model achieves an overall accuracy of 94.58%.

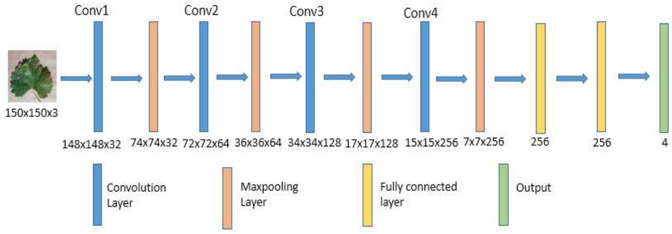


Fig. 6. Schematic representation of CNN model

The literature studies reveal that pre-trained models using transfer learning are an efficient strategy for plant disease classification. Popular pre-trained models such as VGG, ResNet, and DenseNet are used and the experimental results are compared. The images are resized to 224x224, which is the default size accepted by the VGG, ResNet, and Densenet models. The loss and accuracy plotted during different epochs are shown in Fig 7. The experimental results presented in Table 1 show that the DenseNet model outperformed all other models with an accuracy of 98.27%. The classification performance of each model is analyzed using metrics such as confusion matrix, precision, accuracy, recall, and F1-score. The confusion matrix of the model is generated for the test set and is shown in Fig 8. The confusion matrix gives a summary of the predictions against the actual values.

$$Accuracy = (TN + TP) / (TN+TP+FN+FP) \quad (2)$$

$$Recall = TP / (TP + FN) \quad (3)$$

$$Precision = TP / (TP + FP) \quad (4)$$

$$F1\ score = 2 * [(precision*recall) / (precision+recall)] \quad (5)$$

TABLE I. CLASSIFICATION PERFORMANCE OF DIFFERENT MODELS

Model	**Precision**	**Recall**	**F1-score**	**Overall accuracy**
CNN Model	94.60	94.58	94.56	94.58
VGG Model	95.54	95.32	95.32	95.32
RESNET Model	97.11	97.04	97.05	97.04
DENSENET Model	98.31	98.27	98.28	98.27

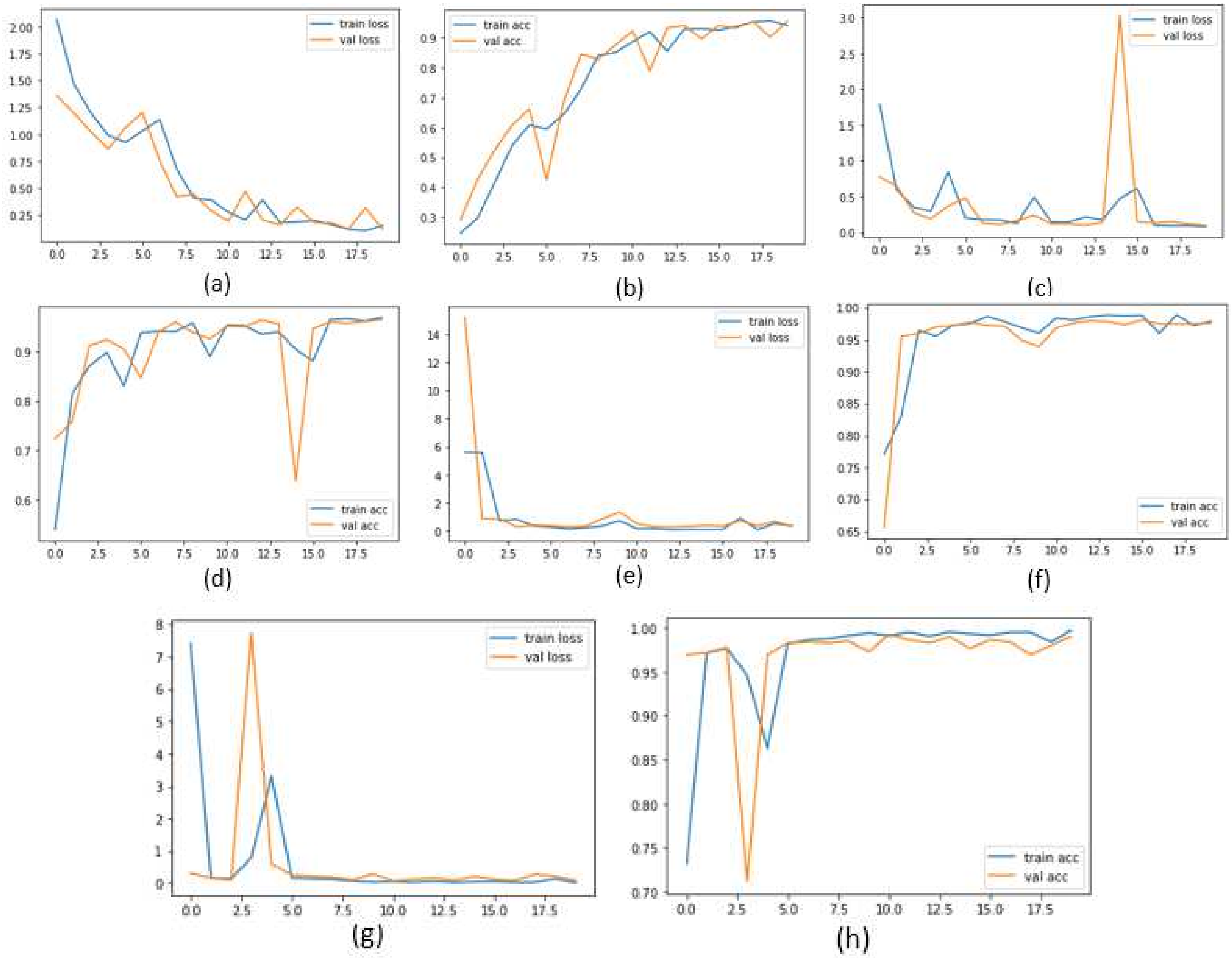
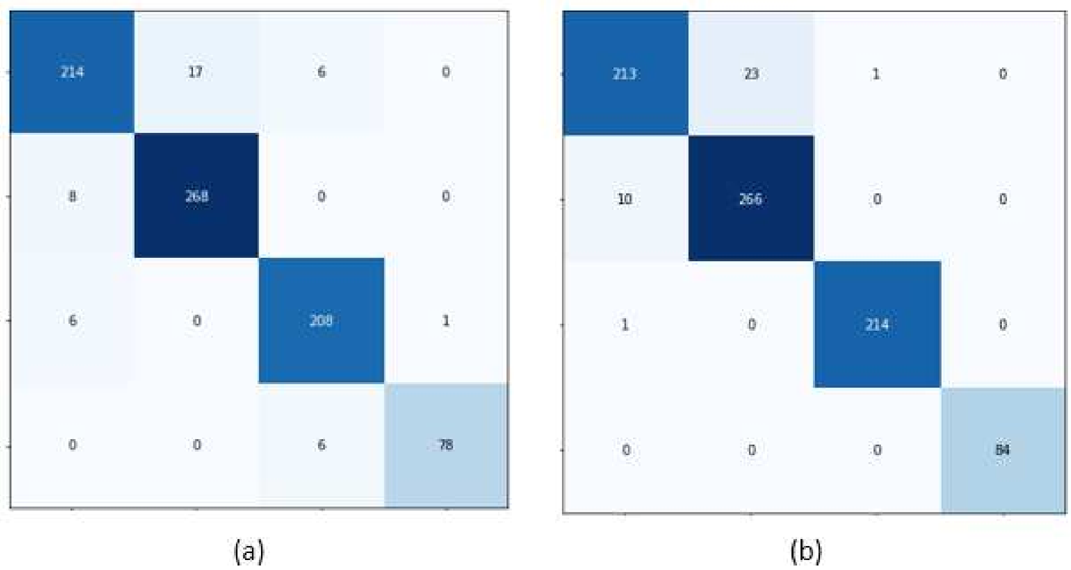
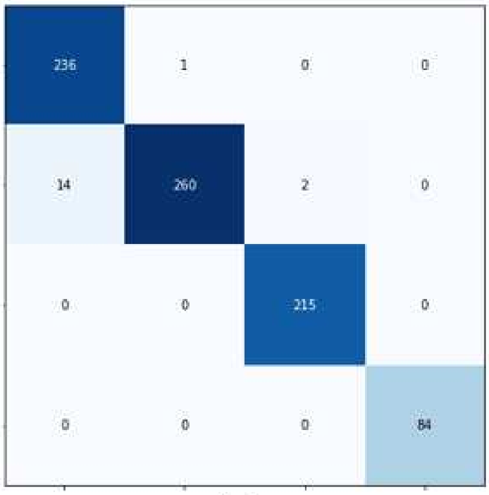
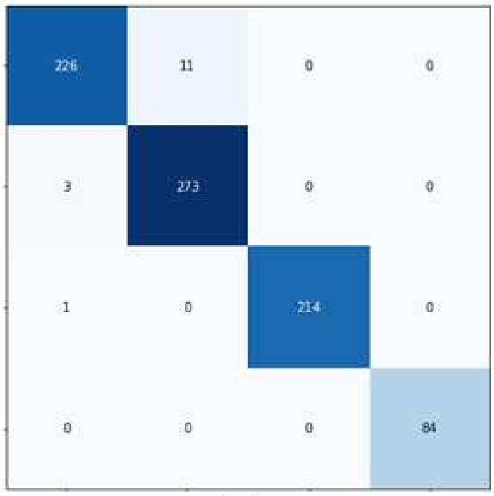


Fig 7 a-b) Loss and Accuracy curves of the CNN model. c-d) Loss and Accuracy curves of the VGG model e-f) Loss and Accuracy curves of the ResNet model g-h) Loss and Accuracy curves of the DenseNet model





(c)



(d)

Fig 7 a) Confusion matrix of CNN Model b) Confusion matrix of VGG Model c) Confusion matrix of ResNet Model d) Confusion matrix of DenseNet Model

V. Conclusion

This study facilitates the early diagnosis of plant diseases to prevent crop loss and the spread of diseases. The CNN model is used to predict different plant diseases correctly. The performance of various pre-trained CNN models such as VGG, ResNet, and DenseNet is observed, and then based on performance metrics, the DenseNet model is found to be more accurate. The model's testing is done using performance evaluation metrics such as accuracy, precision, recall, and F1 score. The DenseNet model achieved the highest accuracy of 98.27%. One of the main problems faced in a larger neural network is the vanishing gradient problem. The ResNet model adds the output of one layer to the next layer, whereas in the DenseNet model, the output feature maps are concatenated with the following future feature maps. Each layer will receive features from the previous layers and pass its features maps to all subsequent layers. Due to that DenseNet model will have features of all complexity and performs well in small datasets. Future works include expand the dataset and increase the number of classes. Another future work is deploying the model into a website/application as it will help farmers/pathologists to identify different diseases using their mobile cameras.

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