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Classification of Plant Leaf Diseases Using Deep Learning Concepts

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Abstract

Agriculture is vital to the economy of a country like India, where 70% of the workforce is employed in this sector. Plants suffering from illnesses experience a significant reduction in output. Delays in the identification of plant diseases lead to decreased yield and plant mortality. The cost of manufacturing is increased since it takes a big number of experts to manually detect plant diseases over several acres of land. The purpose is to summarize a critical challenge in agriculture by automating the diagnosis of plant leaf diseases with the potential to revolutionize crop management. Traditional methods are often time-consuming and complex, leading to healthier crops and a more sustainable future. The proposed work implements a convolutional neural network model, VGG-16 for training the system. The data is pre-processed to meet the requirements of the input. The VGG-16 is compared to other models such as SVM, KNN, and traditional CNN and FCNN.

Keywords: Plant diseases, leaf images, VGG16, pre-trained model, transfer learning, FCNN

INTRODUCTION

India has an arable land area of 159.7 million hectares (394.6 million acres) and is the second largest in the world, after the United States. India is recognized as one of the world's megadiversity centers and as a major hub for the domestication of crop plants. India is home to about 20,000 kinds of higher plants, and its 160 cultivable plant species are spread throughout its many agroecological zones. Undoubtedly, India's primary source of income, particularly for those living in the country's vast rural areas, is agriculture and its related businesses. It adds to the GDP (Gross Domestic Product) as well. Therefore, the concept of sustainable agriculture is crucial for both rural employment and food security. As a result, diagnosis and analysis of diseases in plants becomes a major concern. Traditional methods for identification of plant disease include agriculture professionals, or plant pathologists have traditional inspection to detect leaf disease with naked eye, and another way is to do microscopic analysis of morphology features to identify pathogens. This approach of detecting plant leaf disease traditionally can be subjective, time-consuming, expensive, and requires a lot of people and a lot of information about plant diseases. It is also possible to detect plant leaf diseases using an experimentally evaluated software solution. Deep learning and machine learning have been applied widely in recent years. The goal is to increase profitability, enhance quality, refine efficiency, boost productivity, and strengthen sustainability. Within the fields of computer science and artificial intelligence, machine learning focuses on using data and algorithms to mimic human learning processes, progressively increasing the accuracy of the model. Using ML in agriculture enables more accurate and

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efficient farming with fewer laborers while producing high-quality, high-yield crops. ML is a modern technology that helps farmers reduce farming losses by offering insightful and detailed recommendations regarding the crop. Algorithms that leverage customary approaches to machine learning such SIFT and SVM are frequently used. This strategy demands for more complex calculations that are challenging for online applications. Therefore, the effectiveness of these strategies may only produce a desirable outcome. The complicated use of tools like electromagnetic radiation, IR spectrums, and plant genomes is needed to increase performance and accuracy of feature extraction, but these tools are very expensive for small-scale farmers to utilize for extracting characteristics of plant diseases. Deep learning uses artificial neural network architecture and typically has many more layers to process information. Image detection, image classification, acoustics, and other fields that need to analyze enormous amount of data have all been changed by deep learning. Deep learning has been included in the diagnosis of plant diseases, which has influenced how specialists evaluate data and reach decisions. In the proposed system, we will be measuring the performance of the models SVM, KNN, traditional CNN, FCNN and VGG-16, based on their ability to predict the correct disease. VGG16 has the most accuracy and will be used for the classification of the disease.

PROBLEM STATEMENT

To classify the diseases based on plant leaf images using machine learning and deep learning algorithms and comparing their accuracies and predicting the plant leaf disease using the network with the highest accuracy.

DATASET

This dataset has been generated through offline augmentation of the original dataset, which is available on GitHub. It consists of approximately 87,000 RGB images of healthy and diseased crop leaves, categorized into 38 distinct classes. The source of this dataset is the New Plant Diseases dataset hosted on Kaggle, which originally contains 82,102 healthy and unhealthy leaf images across 38 categories, classified by plant species and disease type. The dataset comprises of 10 classes of five healthy and five unhealthy classes each of leaf images.

OBJECTIVES

The primary objective of this work will be identification of diseases using plant leaf images, and identification of both disease-infected and healthy leaves.

LITERATURE SURVEY

This section gives a detailed literature survey overview. In this we have referred to several papers related to classification and detection. Table 1 represents the literature overview of studies done, images of plant leaf, and the strategies utilized. Some studies are mainly based on various machine learning and deep learning techniques [1–8]. Some papers are based on localization-based classification and hybrid segmentation algorithm [9, 10]. The study by Lee *et al.* is based on the transfer learning model concepts [11]. In the study by Ozguven and Adem, a faster R-CNN has been adapted to detect diseases in sugar beet [12]. Soft computing techniques have been employed for disease detection by Francis and Anoop [13]. Some of the studies are based on the concepts of genetic algorithms and WSN [14, 15]. Mahin *et al.* have used a self-created dataset to do the prediction; this strategy can also be applied in future systems [16].

PROPOSED SYSTEM

The recent years have witnessed rapid development in the sphere of deep learning, especially in the areas of image recognition, natural language processing, speech analysis and other fields. This arises from the efficiency and uniqueness of deep learning in comparison to traditional methods. The techniques employed in deep learning have become more efficient in identifying and diagnosing crop diseases. Image recognition of the crop diseases can aid in cutting down the dependence on agricultural technicians, thereby empowering the farmers to solve the problem at the earliest. Compared with artificial identification, the speed of an intelligent network is much faster than manual detection. And the recognition accuracy of such networks keeps getting higher and higher as it gets more enriched with data and due to continuous development of the work that plans to employ VGG16 for the training of the system. In order to enable the farmers to identify the diseases conveniently and early, this work establishes a system application. The application can identify the crop diseases which aids the farmer to comprehend the situation and take necessary actions to curb it. The system first builds a crop recognition model; then the user can upload the image; the image is transmitted to the back end for processing through the VGG 16 network at the front end. Firstly, the image is processed to meet the model requirements if the image is too large, the input dimensions are reduced which will help in increasing the efficiency. Secondly, to enhance the recognition efficiency of the system, the input image is cut randomly and the pixels are optimized; lastly, the name of the crop disease with the matching highest degree is displayed; once the recognition is completed, if the input image is in healthy state, the output system displays healthy leaf.

ADVANTAGES

- In comparison to manual identification, the speed of intelligent network identification is much faster and the rate of recognition is better.
- The deep learning system can effectively diagnose the crop disease in time, mitigating the loss in yield.
- The deep learning models can reduce the dependence of farmers on the plant pathologists, aiding them monetary benefits.

Proposed System Architecture

In Figure 1, the architecture depicts that the leaf image dataset is collected and loaded. The images in the dataset are resized as 128×128. The data augmentation is performed on the images which creates modified copies of dataset using the existing dataset. Then, the dataset is split into training and validation dataset with the ratio 80:20.

The model is trained for 5 epochs using a batch size of 32. Further, the model is saved as .h5 file and is evaluated which provides with loss and accuracy graph. The diseases are predicted using the model by giving an input leaf image. The name of the healthy or unhealthy leaf is displayed.

Table 1. Summary of the literature survey.

Strategy	**Results**
Resnet-34	The resulting model has an accuracy of 98.7%
The study compared three deep learning models (CNN, VGG16, and VGG19) for the task of plant disease detection	CNN achieved the highest accuracy of 0.97%, followed by VGG16 at 0.96% and VGG19 at 0.95%
The experimentation was done with Detectron2 software library and Faster R-CNN to detect leaf diseases. The 6407 images of dataset were augmented using RoboFlow tool.	For this model, the AP50 was 64.193
The dataset is divided into three for three different plants and CNN is applied on all three datasets separately	The tomato dataset achieved the accuracy of 95%. The pepper bell dataset achieved the accuracy of 98.5%. The potato dataset achieved the accuracy of 98.3%
AlexNet and GoogleNet models	Overall, this work produced an accuracy of 86%. These models are computationally expensive
The algorithms used SVM, k-NN, Fully Connected Neural Networks (FCNN) and CNN.	The error rate for CNN was less than 1%, compared to 8–9% for SVM and FCNN. The error rate was more than 20% for k-NN.
Hybrid Segmentation Algorithm for segmentation of images. Then segmented images were input to CNN for classification.	Results were 75.59%. The dataset imposed limitations on diversity of crops used

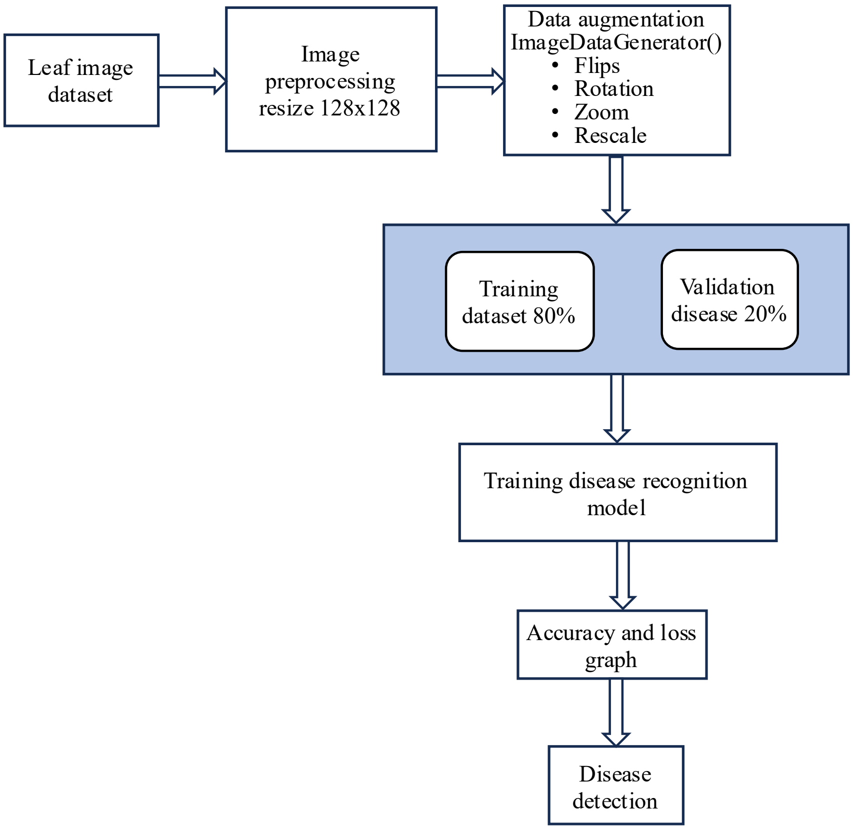


Figure 1. Architecture of the proposed system.

Table 2. Images distribution into different classes.

Class	**Count**	**Type**
Apple_healthy	2008	Healthy
Cedar_apple_rust	1760	Unhealthy
Corn_Common_rust	1907	Unhealthy
Corn_healthy	1859	Healthy
Grape_healthy	1692	Healthy
Grape_Leaf_blight	1722	Unhealthy
Peach_Bacterial_spot	1838	Unhealthy
Peach_healthy	1728	Healthy
Tomato_healthy	1926	Healthy
Tomato_mosaic_virus	1790	Unhealthy
Total	18230	

Table 2 represents the number of images in each class in the dataset. The total number of images present in the dataset are 18230.

In our proposed system, the VGG 16 model is employed for classification of the images of plant leaf diseases. The VGG 16 model is based on the concept of transfer learning. It is a neural network trained on the subset on the ImageNet dataset which has a collection of 14 million images which belong to 22000 categories. It was proposed in the 2015 paper Very Deep Convolutional Networks for Large-Scale Image Recognition, which introduced the VGG architecture known for its use of small convolutional filters and deep network structures.

For experimental purposes, a subset of the dataset was selected, comprising 10 classes, with an equal distribution of five healthy and five unhealthy leaf image categories as shown in Figure 3.

RESULTS ANALYSIS AND DISCUSSION

All the models are trained with the plant leaf dataset and a comparison bar graph is generated for all the five networks i.e., SVM, KNN, traditional CNN, FCNN and VGG-16. The Screenshots are listed in this section. Figure 2 shows the GUI for building models and analysis.

The Figure 4 displays how the proposed model is trained. The training of VGG-16 model is completed and the accuracy is generated. The accuracy secured by the VGG-16 model is 98.27%. Figure 4(a) is used to show the models of SVM, KNN, and FCNN, and for analyzing their respective accuracies for the CNN model with 5 epochs. The SVM, KNN and FCNN models are created successfully, and their accuracies are also calculated.

In Figure 4(b), the dataset is next loaded for building the traditional CNN network which shows all the 10 classes that are to be trained.

The VGG-16 model screenshot is shown in Figure 5 and the prediction of the diseases viz. apple and corn is shown in Figure 6(a and b), respectively.

Table 3 depicts the performance of different classifiers where the train test ratio is 80:20. It can be observed that the pre train model VGG 16 has the highest accuracy followed by CNN, FCNN, SVM and KNN.

Figure 2. GUI for building models and analysis.

Table 3. Overall accuracy of different classifiers.

Name of the Classifier	Accuracy (%)
SVM	84.88
KNN	52.44
FCNN	73.11
CNN	75.65
VGG-16	98.27

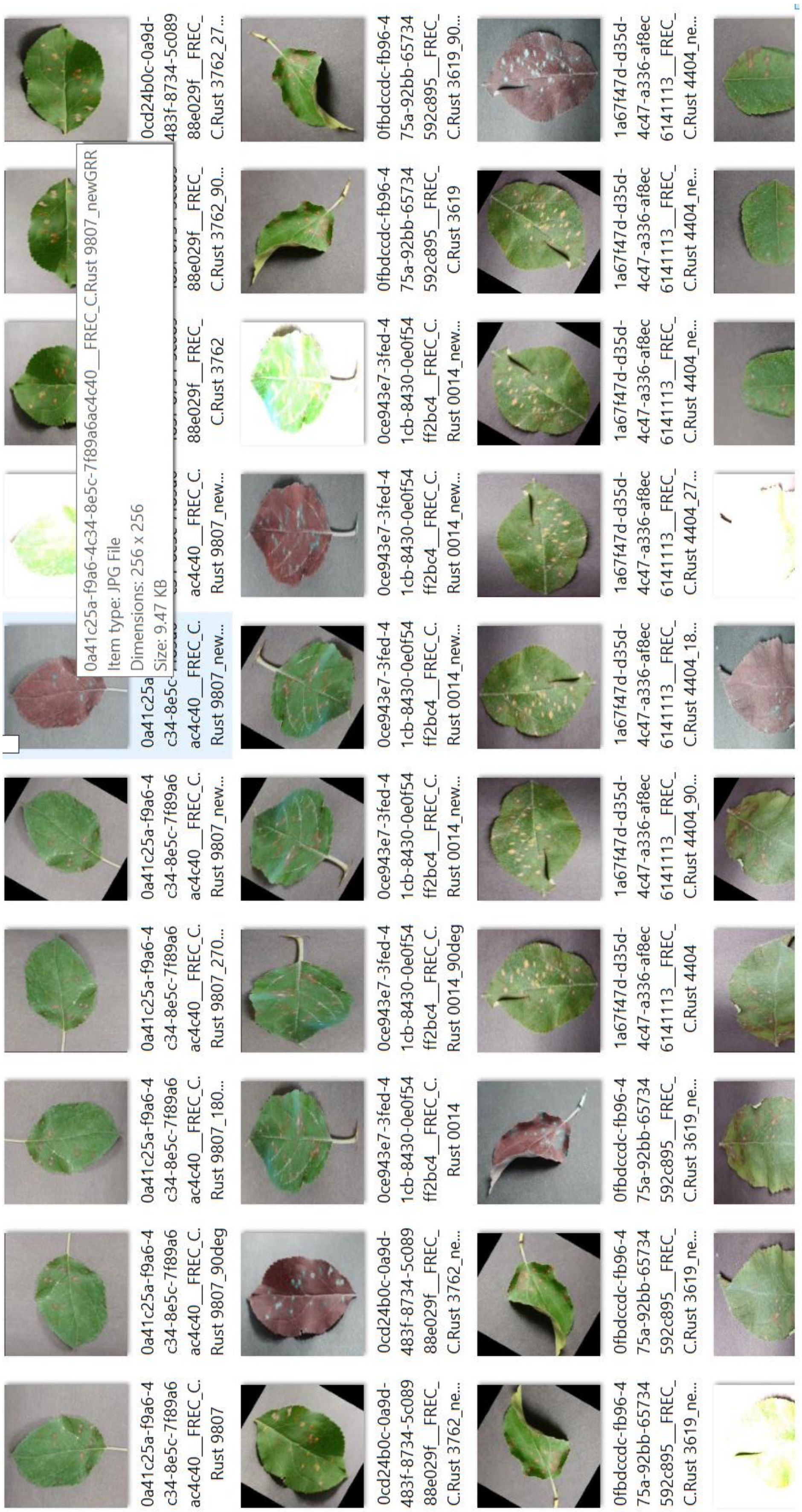


Figure 3. New-plant-disease: dataset.


```
[INFO] Loading Training dataset images...
[INFO] Image Processing completed
[INFO] Training KNN model...
[INFO] Training KNN model created successfully..!
[INFO] Training SVM model...
[INFO]  Training SVM model created successfully..!
[INFO] Training FCNN model...
[INFO]  Training FCNN model created successfully..!
CALCULATING SVM ACCURACY......
84.88888888888889
CALCULATING KNN ACCURACY......
52.44444444444445
CALCULATING FCNN ACCURACY......
73.11111111111111
```

(a)

```
[INFO] Loading Training dataset images...
Apple_healthy
..\PlantDiseaseDetection\dataset\Apple_healthy
Cedar_apple_rust
..\PlantDiseaseDetection\dataset\Cedar_apple_rust
Corn_Common_rust
..\PlantDiseaseDetection\dataset\Corn_Common_rust
Corn_healthy
..\PlantDiseaseDetection\dataset\Corn_healthy
Grape_healthy
..\PlantDiseaseDetection\dataset\Grape_healthy
Grape_Leaf_blight
..\PlantDiseaseDetection\dataset\Grape_Leaf_blight
Peach_Bacterial_spot
..\PlantDiseaseDetection\dataset\Peach_Bacterial_spot
Peach_healthy
..\PlantDiseaseDetection\dataset\Peach_healthy
Tomato_healthy
..\PlantDiseaseDetection\dataset\Tomato_healthy
Tomato_mosaic_virus
..\PlantDiseaseDetection\dataset\Tomato_mosaic_virus
10
```

(b)

Figure 4. (a) Model evaluating the accuracy of SVM, KNN and FCNN, (b) Dataset loading.

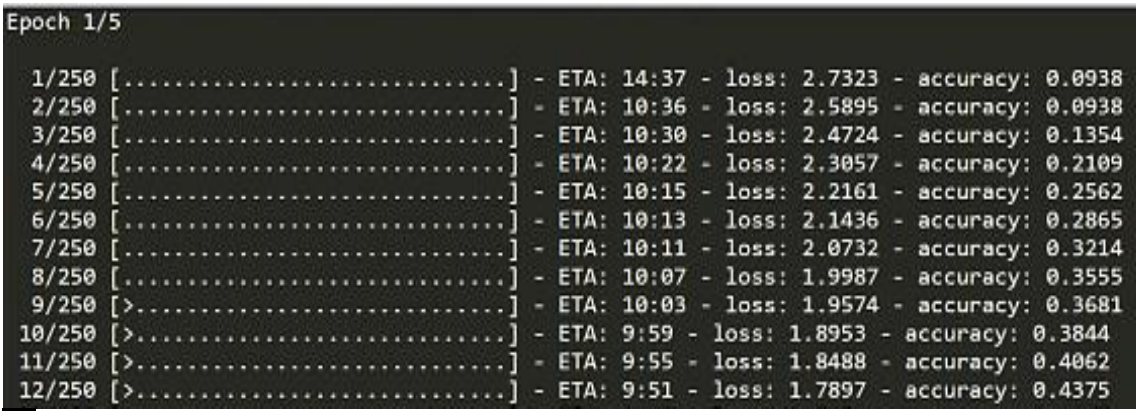
```
Training_VGG16.py
        print(n_classes)
        np_image_list = np.array(data, dtype=np.float16) / 225.0

        x_train, x_test, y_train, y_test = train_test_split(np_image_list, ima
        base_model=VGG16(include_top=False,input_shape=(128,128,3))
        base_model.trainable=False
        classifier=keras.models.Sequential()
        classifier.add(base_model)
        classifier.add(Flatten())
        classifier.add(Dense(10,activation='softmax'))
        classifier.compile(optimizer='adam',loss='categorical_crossentropy',me

        print("[INFO] training network...")

        aug = ImageDataGenerator(
```

(a)



```
Epoch 1/5

  1/250 [..............................] - ETA: 14:37 - loss: 2.7323 - accuracy: 0.0938
  2/250 [..............................] - ETA: 10:36 - loss: 2.5895 - accuracy: 0.0938
  3/250 [..............................] - ETA: 10:30 - loss: 2.4724 - accuracy: 0.1354
  4/250 [..............................] - ETA: 10:22 - loss: 2.3057 - accuracy: 0.2109
  5/250 [..............................] - ETA: 10:15 - loss: 2.2161 - accuracy: 0.2562
  6/250 [..............................] - ETA: 10:13 - loss: 2.1436 - accuracy: 0.2865
  7/250 [..............................] - ETA: 10:11 - loss: 2.0732 - accuracy: 0.3214
  8/250 [..............................] - ETA: 10:07 - loss: 1.9987 - accuracy: 0.3555
  9/250 [>.............................] - ETA: 10:03 - loss: 1.9574 - accuracy: 0.3681
 10/250 [>.............................] - ETA: 9:59 - loss: 1.8953 - accuracy: 0.3844
 11/250 [>.............................] - ETA: 9:55 - loss: 1.8488 - accuracy: 0.4062
 12/250 [>.............................] - ETA: 9:51 - loss: 1.7897 - accuracy: 0.4375
```

(b)

Figure 5. Training VGG-16 model, (a) Code (b) Epochs.

(a)

(b)

Figure 6. (a) Output detected as Apple_healthy, (b) Output detected as Corn_Common_Rust.

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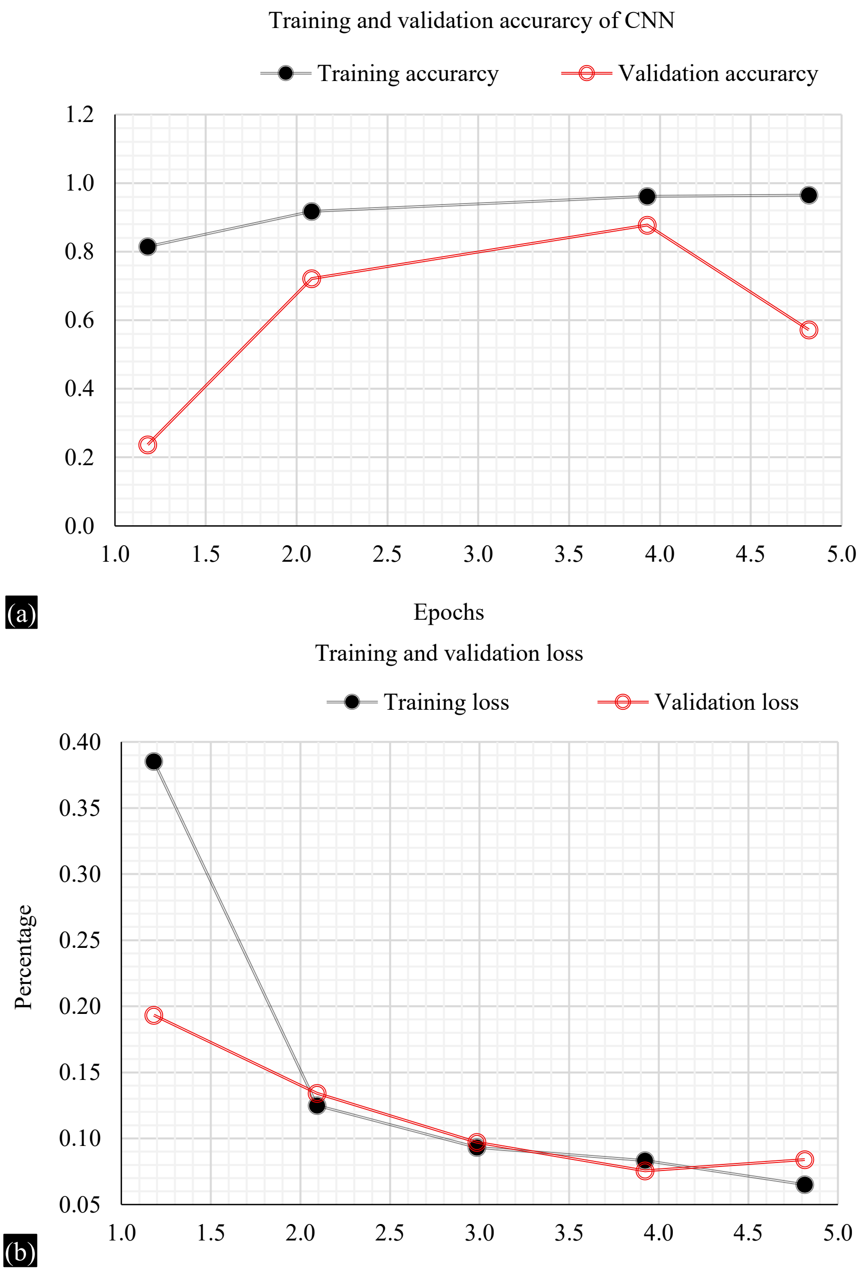

Figure 7. Validation accuracy graph for VGG-16.

Figure 7 shows the accuracy and loss graphs generated for the VGG-16 model. With each epoch, the training accuracy increases and loss decreases.

CONCLUSION AND FUTURE ENHANCEMENT

In this work five diseased and five healthy kinds of crop diseases were studied using the VGG 16 network which was constructed using the concepts of convolutional neural network and deep learning. The theory experiments conducted demonstrated that the model could identify the disease with an accuracy of 98.2%. The results also conclude that the model worked better in comparison to traditional convolutional neural network, FCNN, SVM and KNN. The best accuracy is observed by the VGG-16 model. Thus, pre-trained models can be used to effectively identify the plant diseases thereby aiding the farmers in better agricultural production and hence better livelihood. In further research, more plant species can be obtained for research. There are many more plant diseases that can be detected. Model optimization can also be performed. Other networks should be explored that can give efficient and feasible results. The training time of the model can also be improved by selecting proper arguments provided during the model compilation.

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