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Diagnosis of Major Foliar Diseases in Black gram (*Vigna mungo* L.) using Convolution Neural Network (CNN)

M. Kalpana[1], L. Karthiba[1], K. Senguttuvan[1], R. Parimalarangan[1]

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ABSTRACT

Background: Proper diagnosis of a foliar disease is a prerequisite to undertaking any crop protection strategy under field conditions. Poor diagnosis and a delay in confirmation in turn decrease the crop yield and increase the cost of plant protection. In this background, advanced machine learning techniques were used for diagnosis of major foliar diseases in black gram using image detection. Casually, black gram yields are highly reduced due to anthracnose and powdery mildew diseases up to 40-67%. To address the issues, the advanced disease identification method of Convolution Neural Network (CNN) is proposed for automated diagnosis in its early stages to assist farmers.

Methods: Disease infected leaf samples and their images were collected from different cultivated areas of Tanjore district, Tamil Nadu, India. The image noises were removed and enhanced to improve the accuracy of the training network. A Convolution Neural Network was built with five layers to work on disease images. The first stage of training is to load the image set for training, establish the learning rate, run the optimizer and compile the training convolution model. The final part is to save the loss and accuracy during the training process and evaluate the accuracy of the model. To improve the training learning rate, the Adam optimizer and RMSprop algorithm are used to dynamically adjust the learning rate. The image dataset holds a total of 2002 images of black gram anthracnose and powdery mildew for evaluation.

Result: The experiment result showed that the accuracy of disease detection in black gram is about 92.50 per cent with a Precision: 97.14 per cent, Recall: 87.17 per cent, F1 score: 91.89 per cent which proves that convolutional neural network has a faster training speed and higher accuracy. In addition, the proposed method is less time consuming, an early detection tool for the farmers to identify the anthracnose and powdery mildew in black gram leaf which is essential for the application of proper disease management strategies and reduction of yield loss and aids in promotion of smart agriculture.

Key words: Accuracy, Anthracnose, Black gram, CNN, Datasets, Powdery mildew.

INTRODUCTION

Pulses play a valuable role in food safety and security. It accounts for 7-10 per cent of total food grain production, with an area of around 20 per cent. Black gram (*Vigna mungo* L.) is also known as urd bean, ulundu paruppu, minapa pappu and most daily in-taking legume *via* various cushiness. The total global acreage under pulses is around 93.18 (Mha), with a production of 89.82 (MT) at a yield level of 964 kg/ha. India is the world's largest producer of pulses, with more than 28 million hectares under production. It leads in both area and output, with 31% and 28%, respectively. Our productivity of 885 kg/ha in 2020-21 has also improved dramatically during the past 5 years. In Indian cuisine, it is often used for a variety of dishes. Currently, global-wide pulse production has stagnated and production losses have occurred due to the pest and disease incidences. Especially the yield of black gram is reduced significantly because of the most common diseases, such as anthracnose and powdery mildew. The early and timely detection and diagnosis of these diseases is a challenging factor for enhancement of yield (Channaveeresh and Kulkarni, 2017).

In crop protection, disease diagnosis plays a complex role in agriculture. Due to a lack of awareness among farmers about early detection and diagnosis of crop diseases using scientific based approaches, which results in not able to take proper curative measures and unpredicted yield losses during the cropping period (Malo and Hora, 2020). The use of advanced technologies in crop disease diagnosis will reduce yield loss in agriculture (Priya Rani *et al*., 2022). The advancement of non-destructive detection and early crop disease identification is crucial to the development of precision and ecological agriculture. Furthermore, now it is growing by using advanced technologies (AI-Artificial Intelligence) in agriculture such as rainfall forecasts, time of sowing, irrigation, fertigation, pre-reports of pest and disease incidences and harvesting indications used by

[1]Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India.

Corresponding Author: M. Kalpana, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India.
Email: kalpusiva@gmail.com

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developed countries. But developing countries are establishing these automated technologies in agriculture now. Especially, these automated diagnosis technologies' highly gainful approaches to the farmers' detection and diagnosis of foliar diseases with efficiency in time saving and accuracy (Singh *et al*., 2021).

Under these scientific approaches, there are several proposed ways to identify crop disease, in the field observation for farmers, light spectrum technology by Yang *et al.* (2013) and Zhao. *et al.* (2016), detection based on visible light by Prince *et al.* (2015), traditional image processing by Zhong *et al*. (2017) and deep learning methods by Raza *et al*. (2015). Based on data on rice characteristics, Zhao *et al*. (2018) employed a BP neural network to identify rice leaf curling and the diagnosis accuracy was greater than 90% verified based on 300 data samples. Networks with more layers give better diagnosis performance using convolutional neural networks (CNN). LeCun *et al*. (1998) proposed CNN, which offers a lot of benefits. First, the trained data can be used as the input for CNN and the original data can be used as the output. Second, CNN includes several properties that helps to reduce the complexity of the network and the number of parameters that need to be trained, such as local connection, weight sharing and pool layers. Additionally, CNN can smoothly pan, rotate and zoom picture data. In addition, original images are directly input into CNN for feature extraction without manual operation. After pooling the extracted features, the output layer of a classifier is used to diagnose diseases and give the type of disease. In recent years, much research has been done on crop disease diagnosis using CNN. Krizhevsky *et al.* (2021) successfully identified rice illness using CNN and an AlexNet classifier, obtaining good performance with an accuracy of more than 90%. Deep learning was first applied to crop disease diagnosis by Ren *et al.* (2020) using satellite photos acquired by UAV remote Sensing in the past. In this study, CNN was used to extract characteristics from the photos and by adjusting parameters and refining the network structure, a disease detection model with high accuracy was produced. The accuracy of the constructed model was 97.75% on a dataset of three kinds of crops. CNN is suitable for image recognition, because it has visual information processing.

It was constructed with two distinct deep architectures as described by Anand *et al.* (2020) for identifying the type of infection in tomato leaves. Experiments were conducted using the Plant Village dataset with three diseases, namely, early blight, late blight and leaf mold. The proposed work exploited the features learned by the CNN at various processing hierarchies and achieved an overall accuracy of 98 per cent on the validation sets in the 5-fold cross-validation. According to several evaluation indicators, Li *et al*. (2020) proposed two methods that could outperform other deep-learning models on three different datasets. The combination of shallow CNN and traditional machine learning classification algorithms is a good effort to deal with the identification of plant diseases.

The use of deep learning technology by Ma *et al*. (2018), Rangarajan *et al*. (2018) and Oppenheim *et al*. (2018) to learn plant disease characteristics and use Tensor Flow by Dean *et al*. (2016) to build a convolutional neural network model that could accurately identify disease categories. The efficacy of the suggested approach will be examined using two datasets, namely Plant Village by Zhang *et al*. (2018) and the image database in the crop disease recognition competition in global AI challenge. These two datasets, which are extensively researched in the field of diagnosing agricultural diseases, comprise a variety of leaf photos of both healthy and diseased crops. Bao *et al.* (2021) performed image recognition with the Plant Village dataset with an accuracy of 93.95 per cent. Zhang *et al.* (2021) diagnosed crop disease datasets in the global AI challenge with an accuracy of 83 per cent. The traditional methods usually diagnose disease by observing the morphological characteristics of the diseased black gram. The traditional method depends on the experience accumulated by farmers in past dynasties. Many inaccurate viewpoints may be collected and used to identify diseases. These methods are time consuming and laborious. Furthermore, there are not enough agricultural technicians to identify the disease black gram based on its morphological characteristics. To improve both the accuracy and efficiency of black gram diseases, an accurate, intelligent and less time-consuming Convolution Neural Network (CNN) is used for construction. Keeping this advance engagement in mind, the work was framed for the diagnosis of major foliar diseases in black gram through the advance technology of CNN.

MATERIALS AND METHODS

System description

The materials and methods used in this research are given in this section under sub heads such as Collection of datasets, CNN architecture and Data labeling.

Following are the details of each sub heads. Collection of datasets provides a detailed description of the datasets used in this research. CNN architecture explains all the CNN models used in the experiments, while Data labeling describes how those models were trained or worked out.

Collection of datasets

We conducted a vast survey on the major black gram cultivated fields in areas of Tanjore district in Tamil Nadu, India. Two datasets were collected for major foliar diseases *viz*., anthracnose (*C. lindemuthianum*) and powdery mildew (*E. polygoni*) during the Kharif season. Both diseases appear in all stages of crop growth and aerial parts of the plants exhibit symptoms on hypocotyl regions, branches and stems such as dark brown to black sunken lesions, which are generated during the juvenile stage and die earlier. At the vegetative to reproductive stages of the crop, small and angular lesions arise, mainly close to veins and develop into a grayish white centre with a dark brown or red-dish edge, numerous lesions are also seen on the petioles and stem. At first, tiny water-soaked lesions emerge on the pods, then turn brown and widen to form a circular, sunken patch with a dark centre and bright red or yellow border by Vishalakshi, *et al.* (2017). Finally, it reduced the yield with severe defoliation. It is caused by a unique foliar pathogen, *C. lindemuthianum,* which produces wind-borne conidia for dispersal of the disease. Under this category, thousands (1000) of infected leaf sample images (Fig 1) were collected from different fields and processed further.

For powdery mildew, white superficial fungal mass growth occurred on the adaxial surface of the leaves. Later, these white fungal masses increased rapidly on both sides of the leaves and turned as dull to dark greyish coloured with shriveled, distorted and defoliated. It was caused by foliar pathogen *E. polygoni*, which is spread by air-borne conidia under humid weather conditions LeCun *et al.* (1998). Under this category, disease is diagnosed by collection of 180 diseased leaf images (Fig 2) from the field by continuous capturing and processing.

Fig 1: Image of anthracnose.

Fig 2: Image of powdery mildew.

CNN architecture

Convolutional Neural Network (CNN) approach is a type of feed-forward neural network that utilizes layers, known as convolutional layers. A convolutional layer executes the convolution operator, which involves sliding a small group of weights through the layer's input, as used by LeCun *et al.* (1998). A convolution layer aims to detect local features (disease intensity) from its input image dataset. The size of the input is reduced by the max-pooling layer and the translation invariant of detected features is marginally improved. Finally, a fully-connected layer, also known as a dense layer, is applied to classify the learned features of diseases such as anthracnose or powdery mildew.

The model is configured to take a fixed-size image of 50$\times$50 RGB as an input for processing. The convolution neural network was built with five layers *viz*.; It is a set of learnable filters. Each filter has a small width and height and the same depth as the two input layers (two black gram leaf diseases). The image size is set to 50 (convolution layer); from the convolution layer, a matrix is generated that is smaller in size than the original image. The generated matrix runs through an activation layer (activation layer-Relu); Further, the pooling layer reduces the size of the matrix. A filter is passed over the result obtained from the previous layer and selects one number out of each group of values. Max pooling is used, which helps the network to train faster and focus on the important features of the diseased leaf images (pooling layer); finally, this layer adopts the features of a multilayer perceptron structure. The input obtained is a one-dimensional vector representing the output of the previous layer. Its output is a list of probabilities for different labels attached to the images of anthracnose and powdery mildew.

Data labeling

The label with the highest probability is the classification label (fully connected layer). After the first stage of training, load the images set for training, set the learning rate, optimizer and compile the training convolution model. Final

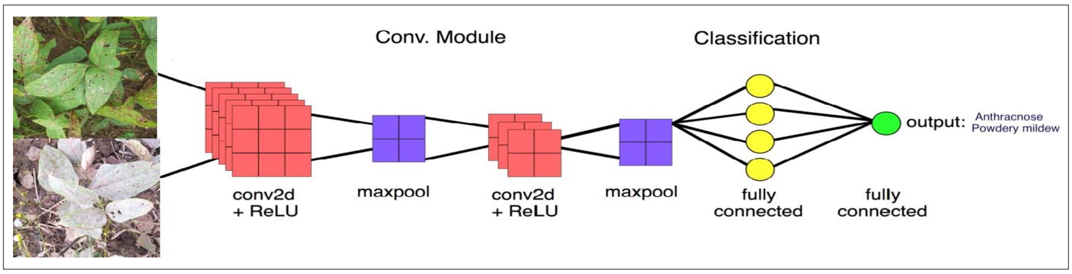

Fig 3: CNN architecture for black gram disease diagnosis.

part is to save the loss and accuracy during the training process and evaluate the accuracy of the model. To improve the training learning rate Adam optimizer and RMSprop algorithm are used to dynamically adjust the learning rate. The learning rate LR = 1e-3. The architecture of the model for a CNN is shown in Fig 3.

Training

The collected black gram image from the field is processed and enhanced images are used for training and testing the convolution neural network model. 80 per cent of the data are taken as training and 20 per cent is used for testing the model. Number of images of leaf diseases (anthracnose and powdery mildew) are 2002. The training images are 1605 and test images are 397. Both training and testing of the black gram leaf disease model were implemented in Python using Keras and Tensor Flow frameworks by using iterations between testing and validations.

Performance metrics

With the increase in iterations, the accuracy of training and verification increases step by step, tends to be stable after 10 iterations and reaches a satisfying level of accuracy. At this time, the convolution rate of the super convolution parameter set has been accurately adjusted by using the number of times in the training set. Finally, after all the iterations are completed, it correlates with accuracy. Additionally, it can also be seen intuitively from the loss curve that the loss rate of training and verification decreases with the increase of iteration times, tending to a stable state after, as shown (Selvaraj *et al*., 2019).

RESULTS AND DISCUSSION

The experiment was conducted using Python programming and 10 iterations were carried out on the black gram disease image dataset with 1605 training set samples and 397 verification set samples in total. The prediction by the CNN model using python programming is shown in Fig 4. The accuracy and loss are shown in Fig 5 and 6; It could be seen that the blue curve in the figure is the training set and the red curve is the test set.

In order to verify the effectiveness of the proposed model, a CNN model was constructed for the image dataset of Anthracnose disease in black gram and metrics such as precision of 89 per cent, recall of 98 per cent and f1 score of 93 per cent were found.

CNN model was constructed for the image dataset of powdery mildew disease in black gram and metrics found such as precision of 97 per cent, recall of 87 per cent and f1

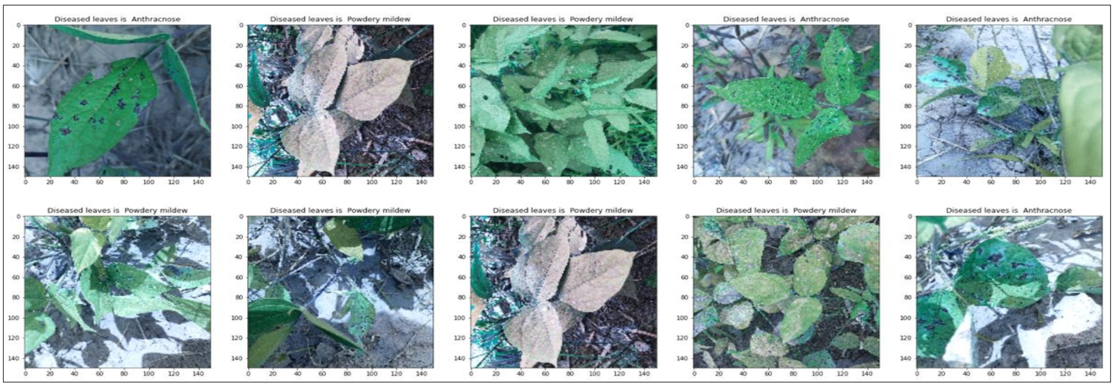

Fig 4: The prediction of black gram disease using CNN model.

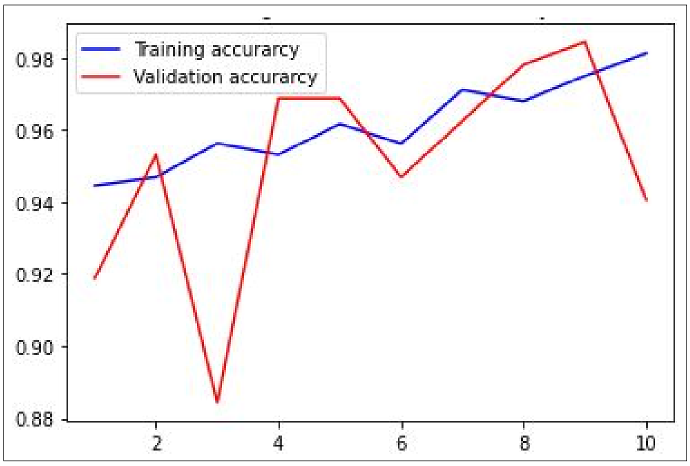

Fig 5: Training and validation accuracy.

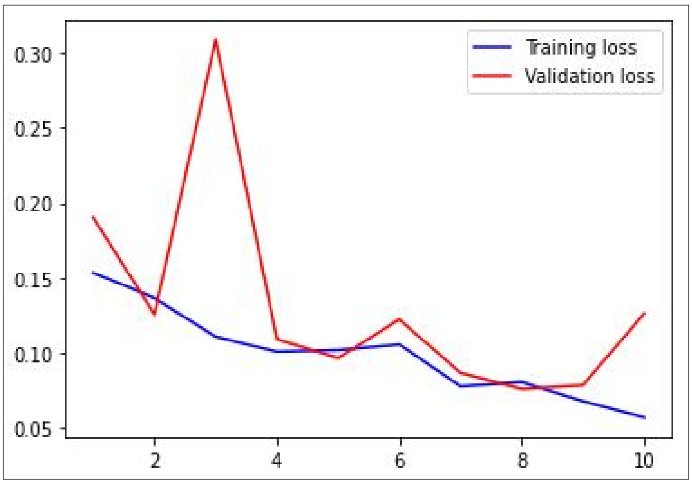

Fig 6: Training and validation loss.

Table 1: Precision, Recall and F-score (%) of CNN model for black gram disease.

Disease	Precision (%)	Recall (%)	f1-score (%)
Anthracnose	89	98	93
Powdery mildew	97	87	92
Overall	97.14	87.17	91.89

score of 92 per cent. The overall metric for the proposed model, precision was 97.14 per cent, recall was 87.17 per cent and f1-score was 91.89 per cent as shown in Table 1.

In this experiment, the accuracy of the model reached about 92.50 per cent for black gram leaf diseases. The experimental results showed that the improved CNN model proposed in this paper had better performance than the traditional image recognition model, Similar results were also found by Selvaraj *et al*. (2019) who found that pest and disease incidence in banana were diagnosed using the CNN model with 90 per cent accuracy.

CONCLUSION

Continuously, in crop disease management, foliar diseases are highly tragic in nature due to their rapid epiphytotic nature and the occurrence of yield loss has been highly maximized. Commonly, anthracnose and powdery mildew cause 40-67 per cent yield loss in black gram. It occurred due to the lack of advanced tools for disease diagnosis. This CNN-based study was used to diagnose diseases such as anthracnose and powdery mildew in black gram. The model investigated anthracnose and powdery mildew diseases in black gram and suggested technical features of the models, described picture sources and reported overall correctness. This study is an initial step in a progressive approach to the diagnosis of foliar diseases in crops. Furthermore, the proposed method is a time-saving early detection tool for farmers to identify anthracnose and powdery mildew diseases in black gram leaf and promoting smart agriculture. Results of this experiment revealed that the convolutional neural network has a faster training speed and a higher accuracy of 92.50 per cent. CNN requires several training data sets to produce accurate results and expanding the number of datasets improves the model's accuracy. Future investigation of this research will focus on all major diseases in black gram.

Conflict of interest: None.

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