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Detection and Classification of Yellow Mosaic Disease in *Vigna mungo* using Convolutional Neural Network Deep Learning Models

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ABSTRACT

The yield of the black gram crop is negatively impacted by Yellow Mosaic Disease (YMD). Both quantity and quality of the black gram suffer significantly from this disease. Accurate diagnosis, flawless identification, and early detection guide the grower for proper and timely management of the disease. Deep learning-based pre-trained models have revolutionized the classification and identification of plant leaf disease in recent times. In the present study yellow mosaic disease of black gram has been classified using four deep learning models namely; DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet. A total of 1100 images were collected from field experiments for each of three classes namely healthy, moderate and susceptible plants. During the field investigation, datasets with images of three classes; healthy, moderate, and susceptible were collected, pre-processed, and augmented to create a set of 1100 images of each class. Seventy percent of the images were used for the training of the models and thirty percent of the images were used for validation. The results obtained for different deep learning architectures DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet showed validation accuracy and loss scores of 96.09, 60.74, 94.41, and 93.85%, and 0.2319, 0.6923, 0.2429 and 0.1399, respectively. For the YMD classification in blackgram, DarkNet-19 showed the highest accuracy and SqueezeNet showed the lowest accuracy.

Key words **:** *Blackgram, CNN, Deep learning, Leaf disease, Model, etc.*

Introduction

One of the most important issues with agricultural production is the problem of disease and pests. Numerous studies have revealed that plant diseases have a significant impact on agricultural production. Eliminating plant diseases considerably raises the yield's quality. There is a lot of potential for rapid sickness detection and prevention in plants. The primary factor contributing to the crop's low yield is its susceptibility to weeds, diseases, and pests caused by fungus, viruses, and bacteria. Most of these plant diseases that affect agricultural output are viral infections (Nene, 1973). It causes highly significant diseases, decreased seed quality and output, and economic losses in Blackgram. Plant viral infections significantly diminish the economic value of many pulse crops by reducing seed output and quality. A severe production bottleneck for the blackgram crop, Yellow Mosaic Disease (YMD), which is caused by the virus Mungbean Yellow Mosaic India Virus (MYMIV) (Basak *et al*. 2004), can result in yield reductions of up to 100%. The virus, which is spread by whiteflies, is a member of the genus Begomovirus (*B. tabaci* Gennadius), which belongs to the family Geminiviridae (Varma *et al*., 2003; Sudhir *et al.,* 2022).

Various methods and techniques have been created to halt agricultural loss brought on by various diseases. Whatever the method, the first step to successful disease care is accurate disease detection at the site of occurrence. The capacity of the deep learning detection method to quickly detect diseases in plant leaves shows significant promise. Deep learning is the term for machine learning that has multiple levels. The output of the level before is the input for every level. While it is learning, the deep neural network autonomously acquires the characteristics of the input sample. A convolution neural network (CNN), a type of deep neural network, uses relatively little pre-processing to recognise and classify objects. The final layers of a CNN are convolutional layers, pooling layers, activation function layers, completely linked levels, and Soft Max layers. For the diagnosis of leaf diseases in plants, many deep learning models, such as AlexNet, ResNet50, Google Net, VGG 16, SqueezeNet, DenseNet-19, etc., can be used. Machine learning methods have recently drawn a lot of interest in the classification of diseases (Sudhir *et al.*, 2022). Various types of activities, including computer vision, audio processing, natural language processing, and agriculture, employ deep learning techniques (Huang *et al.,* 2017; He *et al.* 2016; Deng and Hu, 2014; Mohanty *et al.* 2016). Different deep learning architectures have been developed by researchers, including AlexNet (Krizhevsky *et al.,* 2012), GoogLeNet Inception V3 (Szegedy *et al.*, 2015), VGG net (Simonyan and Zisserman, 2015), Microsoft ResNet (He *et al.,* 2016), Inception V4 (Szegedy *et al.,* 2016), and DenseNets (Huang *et al.* 2017), SqueezeNet (Landola *et al.,* 2016), DarkNet-19 (Redmon and Farhadi, 2017), etc. Mohanty *et al.* (2016) used deep learning techniques to create a smartphone-based disease diagnosis system. With datasets of 54,306 photos of diseased and healthy plant leaves, the convolutional neural network was utilized to train the model. For the categorization of plant diseases, two architectures, AlexNet and GoogLeNet, were assessed. Various deep learning models were employed for categorizing plant diseases by Sladojevic *et al.,* 2016, their models could classify the 14 types of plant diseases with an average accuracy of 96.3%. Edna *et al.* (2019) evaluated the performances of different deep learning architectures, VGG 16, Inception V4, ResNet-50, 101, 152, and DenseNets-121 for the classifications of 38 classes of 14 plants from plant village datasets. In all the networks, DenseNets achieved the highest accuracy level of 99.75 compared to others. Subetha *et al.* (2021) compared the performance of two deep learning models ResNet-50 and VGG-19 for the classification of leaf disease in apples. A total of 3651 images were used in the classifications and the model could predict the leaf disease with an accuracy of 87.7%. Keeping all this in mind, a study was planned to classify the YMD in blackgram. In the present study, DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet were used in an effort to classify the YMD in blackgram. The classification of the images will provide a platform for the computer-aided diagnostic system development for the categorization of different levels of disease. In this regard, this will be the first step in this direction.

Materials and Methods

The dataset for deep learning image classification was generated during field experimentation of blackgram at ICAR-Indian Institute of Pulses Research, Kanpur. Different classes of images namely healthy, moderate and susceptible plants were captured and a total of 1100 images of each class were formed after applying pre-processing and augmentation (Fig. 1). For the study of Mungbean Yellow Mosaic India Virus (MYMIV), different blackgram genotypes were classified using the YMD disease rating scale of 1-9 (Anonymous, 2021). Plants were categorized as healthy, moderate, and susceptible if their yellow leaf mottling covered 0-10%, 10%–30%, and 30-100% of the leaf area, respectively. The MATLAB software was used for the classification of images employing the different pre-trained deep learning models viz; DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet. For the training of models 70% of image datasets were used, while for the validation and testing 30% of datasets were used. The image input size for different models DarkNet-19, Squeeze Net, Alex Net, and GoogLe Net were 256x256X3, 24x224x3, 227x227x3, and 224x224x3 respectively. The model was fine-tuned for the train-

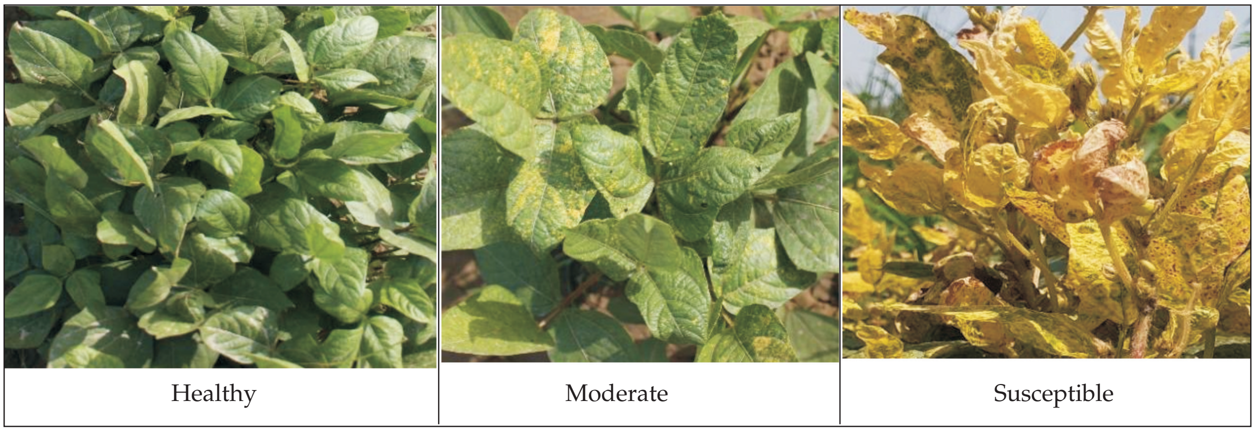

Fig. 1. Different classes of blackgram disease images used for the study

ing and Stochastic Gradient Descent with Momentum (SGDM) solver with a learning rate of 0.001. The detailed flowchart of the process is given in the Fig. 2. For the training of all the models, the maximum number of epochs of 30 with a validation frequency of 50 and a minimum batch size of 128 was taken (Table 1).

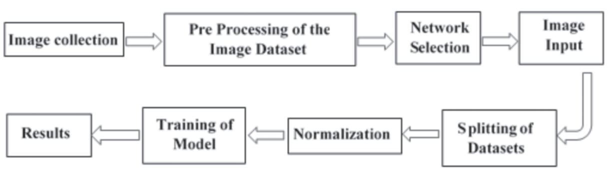

Fig. 2. Flowchart of the methodology followed in the training of the deep learning models

Results and Discussion

Different deep learning models viz; DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet were employed and trained for the image classification of datasets with three classes of YMD images of blackgram namely; healthy, moderate and susceptible. Accuracy measure and categorical cross-entropy loss (loss) were used for the evaluation of the performance of different deep learning models. Data were presented in the form of graphs, and each model's performance in this study was assessed in terms of accuracy and loss. Every experiment was run for 30 epochs, with 16 iterations per epoch and a maximum number of iterations of 480. The Stochastic Gradient Descent with Momentum (SGDM) solver with a 0.001 learning rate was used for the training of different models, since SGDM runs more quickly and converges more easily (He *et al*., 2016). For each network, the results of each experiment are displayed as a separate graph (Figs. 3, 4, 5, and 6). DarkNet-19, AlexNet, and GoogLeNet deep learning architectures displayed validation accuracy levels of 96.09, 94.41, and 93.85%, and SqueezeNet, showed a validation accuracy level of 60.74% (Table 2). The validation loss for DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet was observed as 0.232, 0.692, 0.243, and 0.140. The training accuracy for DarkNet-19, SqueezeNet, AlexNet, and GoogLeNet architectures were found as 99.22, 62.50, 99.22, and 99.22% respectively whereas training loss was observed as 0.011, 0.704, 0.015, 0.031. The DarkNet-19 architecture took the highest computational time of 14677 seconds for training while AlexNet took the lowest computational time of 2910 seconds (Table 2). Previous work-related to deep learning models showed similar results for other crops. Edna *et al.*, 2019 classified the 14 plant diseases with 38 classes

Table 1. Different deep learning models employed in the study

Models	Input Image Size	Max. No. of epoch	Validation frequency	Learning	Solver rate	Min. Batch size
Dark Net-19	256x256x3	30	50	0.001	sgdm	128
SqueezeNet	224x224x3	30	50	0.001	sgdm	128
AlexNet	227x227x3	30	50	0.001	sgdm	128
GoogLeNet	224x224x3	30	50	0.001	sgdm	128

in plant village datasets using six different deep learning networks, it achieved the highest accuracy of 99.75% for the DenseNet-121 model. Subetha *et al.*, 2021 classified apple leaf disease using two deep learning models; VGG-19 and ResNet-50 and achieved average accuracy of 87.7%.

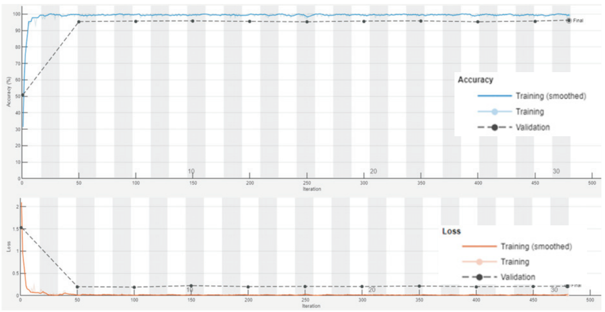

Fig. 3. Performance of DarkNet-19 deep learning model for YMD image classification

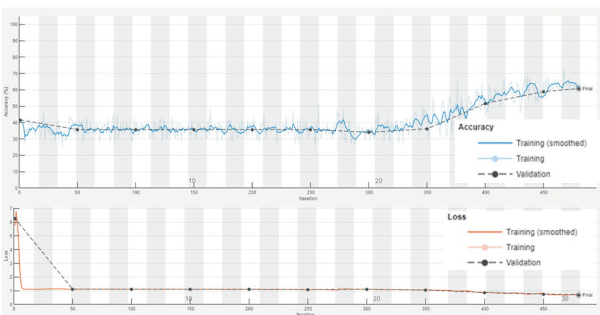

Fig. 4. Performance of the SqueezeNet deep learning model for YMD image classification

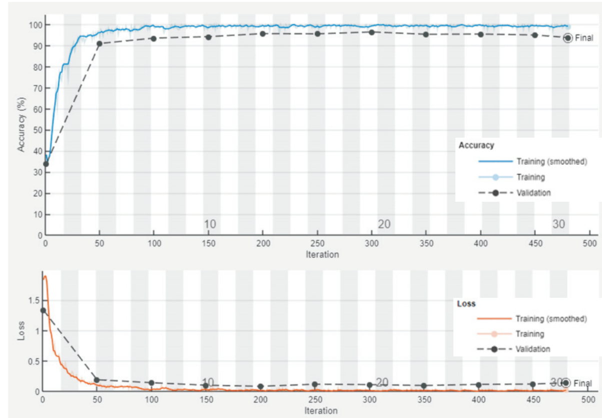

Fig. 5. Performance of the GoogLeNet deep learning model for YMD image classification

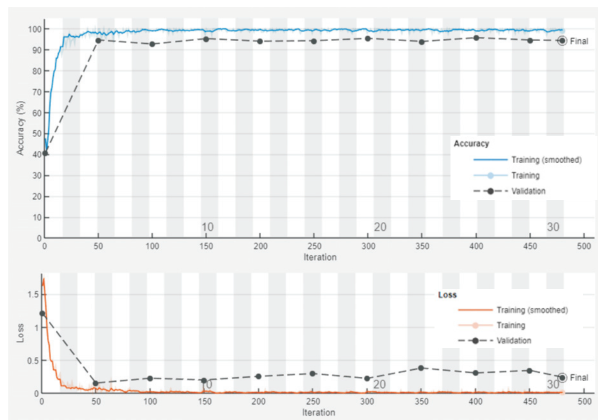

Fig. 6. Performance of the Alex Net deep learning model for YMD image classification.

Conclusion

The image-based classification and identification of diseases of plants have gained due attention in recent times. Different deep learning convolutional neural network architectures have showed tremendous potential to classify and identify diseases in plants based on image datasets. In the present study, four different types of deep neural networks namely; GoogLeNet DarkNet-19 SqueezeNet AlexNet were used for the image classification of the YMD in blackgram. Different deep learning pre-trained models used in this study showed promising results in classifying the different levels of disease infestation of YMD in blackgram. The validation accuracy levels in the case of deep learning architectures were observed as 96.09, 60.74% 94.41, and 93.85%, respectively. The training accuracy was near to 99% in the case of DarkNet-19, AlexNet, and GoogLeNet. In the case of SqueezeNet, training accuracy level was nearly 62%. The DarkNet-19 showed the highest accuracy levels of 96.09%, and

Table 2. Performance parameters for different deep learning architectures

Models	Training accuracy (%)	Training loss	Validation accuracy (%)	Validation loss	Time for training (s)
DarkNet-19	99.22	0.011	96.09	0.232	14677
SqueezeNet	62.50	0.704	60.74	0.692	4472
AlexNet	99.22	0.015	94.41	0.243	2910
GoogLeNet	99.22	0.031	93.85	0.140	7492

SqueezeNet showed the lowest validation accuracy levels of 60.74%, compared to the different models used in this study. In all the networks under this study, AlexNet took the least computational time of 2910 seconds and DarkNet-19 took the longest computational time of 14677 seconds. These architectures can be utilized for app-based disease monitoring, classification, and identification of diseases in different crops. Future work is required for better optimization of these networks and to reduce the computational time.

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