BGCNN: A Computer Vision Approach to Recognize of Yellow Mosaic Disease for Black Gram

Rashidul Hasan Hridoy and Aniruddha Rakshit

Abstract The yellow mosaic disease is a common black gram leaf disease that causes severe economic losses to local farmers and a hindrance to healthy production which can be prevented by computer vision based fast and accurate recognition system. In this paper, Black Gram Convolutional Neural Network (BGCNN) has been proposed for the recognition of this disease, and the performance of BGCNN has compared with the state-of-the-art deep learning models such as AlexNet, VGG16, and Inception V3. All the models have trained with original dataset having 2830 images and expanded dataset generated with image augmentation having 16,980 images that increase test accuracy of all the models significantly. BGCNN realizes accuracy of 82.67% and 97.11% for the original and expanded dataset, respectively. While, AlexNet, VGG16, and Inception V3 have achieved 93.78%, 95.49%, and 96.67% accuracy for the expanded dataset, respectively. The obtained results validate that BGCNN can recognize yellow mosaic disease efficiently.

Keyworks Yellow mosaic disease · Leaf disease · Black gram · Disease recognition · Computer vision · Convolutional neural networks · Deep learning · Transfer learning

1 Introduction

Black gram (scientific name: *Vigna mungo*) is widely used in Southeast Asian cuisine which is a remarkably prized pulse of this region. It is a type of bean, also known as black lentil. It is very nutritious, from ancient times, black gram has been cultivated. A remarkable number of south Asian farmers such as Bangladesh, India, and Nepal are engaged with black gram cultivation. Besides these countries, it is also cultivated

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in the Caribbean, Fiji, Mauritius, Myanmar, and Africa. In medieval times, black gram is also used in the construction of the medieval crucible [1]. Cultivation of black gram is very easy and also provides a high investment return. Black gram has tremendous numbers of health benefits. It has an amazing ability to boost energy and improve immunity, also very helpful for psoriasis patients, as it reduces inflammation. For centuries, the black gram was remarkably used in skin and hair treatment which is the powerhouse of antibacterial properties that reduces acne. Moreover, it helps to control sugar levels, improves digestion and blood circulation, and contains various types of minerals that improve bone mineral density, also helpful for arthritis and osteoporosis patients. Black gram provides instant energy that strengths the nervous system and contains potassium that helps to control high blood pressure by preventing the constriction of blood vessels. Besides these health benefits, it also shows significant performance in both weight loss and gains, black gram oil is a traditional remedy for joint pain. Table 1 shows all the nutrition values of black gram after drying in the sun per 100 g [2].

Plants of a black gram can be affected by different kinds of diseases such as leaf spot, yellow mosaic disease, bacterial leaf blight, anthracnose, powdery mildew, rust, etc. Among these, yellow mosaic disease is the most common disease found in various areas of Bangladesh. A study conducted in Bangladesh found that 63% of farmers continuing black gram cultivation for higher yields and income. Besides 33% of farmers want continuing cultivation as its cultivation is very easy and not costly [3]. Initial symptoms of the yellow mosaic disease appear on young leaves of black gram with light scattered yellow spots. Day by day size of spots increases size, then some leaves completely turn yellow. Necrotic symptoms are also found in affected leaves. Affected plants become stunted and take more time to mature. These plants produce very few flowers. Pods of diseased plants turn in yellow [4]. Yellow mosaic is the most vulnerable disease than other diseases which decreased pod size and quality, affected plants contain fewer and smaller seeds also. In recent times, computer vision has shown surprising performance in various disease recognition related tasks such

Table 1 Nutritional values of raw black gram

Constituents	Approximate composition	Constituents	Approximate composition
Energy	341 kcal	Thiamin	0.27 mg
Carbohydrates	58.99 g	Zinc	3.35 mg
Protein	25.21 g	Sodium	38 mg
Total fat	1.64 g	Potassium	983 mg
Dietary fiber	18.30 g	Calcium	138 mg
Folates	216 mg	Copper	0.98 mg
Niacin	1.45 mg	Iron	7.57 mg
Pantothenic acid	0.91 mg	Magnesium	267 mg
Pyridoxine	0.28 mg	Phosphorus	379 mg

as leaf disease, fruit disease, crop disease, skin disease, etc. Convolutional Neural Network (CNN) is now widely used for recognizing various leaf diseases such as jute, cucumber, rice, wheat, grape, pumpkin, and tomato, etc. To recognize the yellow mosaic disease of black gram, CNN is used in this study. With minimal error, the proposed BGCNN recognizes yellow mosaic disease by classifying black gram leaf images. According to the experimental results, the BGCNN model has achieved 97.11% test accuracy, which is better than other classic models. In addition, after data augmentation, using a dataset of 16,980 images of black gram leaves, the accuracy increases by 14.44%. The performance of BGCNN is compared with state-of-the-art CNN architectures such as AlexNet, VGG16, and Inception V3. We have developed a variant of CNN architecture that consists of convolution, max pooling, and fully connected layers from scratch with fewer parameters which has achieved greater accuracy than other state-of-the-art CNN models. The major contributions are:

- Our proposed CNN architecture, namely, BGCCN has been developed from scratch to recognize the yellow mosaic disease of black gram.
- A new dataset of black gram leaves has been used in this study.
- Moreover, existing CNN models such as AlexNet, VGG16, and Inception V3 have also been used with the transfer learning approach.

The remainder of this study is organized as follows. Section 2 discusses the literature review. The dataset, deep neural network architectures, and experiment are given in Sect. 3. The results obtained in the study are given and discussed in Sect. 4. Finally, the study is concluded with Sect. 5.

2 Literature Review

A remarkable number of researchers have made enormous efforts to detect diseases of the leaf to minimize the damage of diseases. In the paper, Mia et al. [5] have used the support vector machine (SVM) to classify four diseases of the mango leaf and achieved an average of 80% accuracy. K-means clustering has been used for extracting the interesting region of leaf from L*A*B color space. Gray-Level Cooccurrence Matrix (GLCM) method has been used for extracting 13 features from the diseases affected region. To recognize two diseases of the coffee leaf, Sorte et al. [6] have compared the performance of Texture Based Disease Recognition (TBDR), and Deep Learning Disease Recognition (DLDR) approach. In TBDR, texture attribute vectors have been used and Patternnet feedforward neural network for training and testing. To extract statistical attributes GCLM has been used. They have obtained the best result in TBDR using the Local Binary Pattern (LBP). A modified AlexNet neural network has been used directly to the sample images in DLDR. This approach has performed better than TBDR, the Kappa coefficient is 0.970, and sensitivity is 0.980. Han and Watchareeruetai [7] have used AlexNet, VGG16, Inception, Xception, ResNet50, MobileNet, and MobileNetV2 to classify six nutrient deficiencies in Black Gram, and ResNet50 has performed best generalization performance with data augmentation. Precision, recall, f-measure, and test accuracy of ResNet50 are 68.01%, 64.39%, 66.15%, and 65.44%, respectively. Liu et al. [8] have proposed a CNN model named Dense Inception Convolutional Neural Network (DICNN) to diagnose six diseases of the grape leaf and achieved an accuracy of 97.22%. The performance of both Adam and SGD optimization algorithms has been analyzed, and with the same learning rate, SGD has performed better. With the dense connection, DICNN has performed better than without the dense connection. In this research, recognition performance of pre-trained models VGG16, GoogLeNet, ResNet34, DenseNet169, UnitedModel, and AFGDC is 88.96%, 94.25%, 94.67%, 94.89%, 96.58%, and 92.33%, respectively. Atila et al. [9] have analyzed the performance of EfficientNet, AlexNet, ResNet50, VGG16, and Inception V3 models to classify 26 leaf diseases of 14 plants. EfficientNet group consists of 8 models, these are B0, B1, B2, B3, B4, B5, B6, and B7. The input size of B4 and B5 of EfficientNet architecture model is 380×380 and 456×456 pixels, respectively. In the original dataset B5 model has achieved the highest accuracy of 99.91%. But B4 model has achieved the highest accuracy of 99.97% in the augmented dataset. In both types of datasets AlexNet has achieved the lowest accuracy, but while training it has taken the lowest time per epoch. Using shape, color, and texture features of leaves, Rao and Kulkarni [10] have achieved 93.18% accuracy. But using only the shape feature, their classifier has gain 91.74%. Using the GLCM feature, Gabor feature, and Curvelet feature extraction, a combined feature extraction model has been proposed in their study. For classification, the neuro-fuzzy classifier has been used to classify leaf diseases in their research. Based on multiple linear regression, Sun et al. [11] have proposed a disease recognition system for plant disease recognition. An improved histogram segmentation method has been introduced that can accurately calculate the threshold automatically and multiple linear regression and image feature extractions have been utilized in their research. In another research work, Mohanty et al. have used deep learning to detect plant diseases based on leaf image using 38 classes [12]. Their proposed model has achieved 99.35% accuracy on the test set, it can identify 26 diseases of 14 crop species. GoogLeNet architecture has performed better than AlexNet in their study. Three versions of the dataset have been used, and those are color, gray-scale, and segmented. Chandy has used deep learning for pest infestation identification [13]. Shakya have used SVM, KNN, random forest, and discriminant analysis to analyze image classification techniques based on artificial intelligence [14].

As a matter of fact, we come to know that not a single work has been introduced for yellow mosaic disease recognition using any computer vision approach and this is the first attempt to recognize this disease using state-of-the-art CNN models. Hence, it is essential to recognize yellow mosaic disease through a computer vision approach that will assist farmers to maintain the standard level of nutrition and enhance production by taking precautions for affected leaves of black gram.

Fig. 1 Examples of each class of black gram leaf dataset, **a** yellow mosaic disease, **b** healthy leaf, and **c** miscellaneous

3 Materials and Methods

3.1 Black Gram Leaf Dataset

From five black gram plantation farms, images of the dataset were acquired with smartphone camera. Three representative images of the black gram leaf dataset belonging to each class are shown in Fig. 1. A total of 2830 images have obtained belonging to 3 classes, 43.46% of those were affected with the yellow mosaic disease. Dimensions of captured images were 4160×3120 pixels, both horizontal and vertical resolution was 96 dpi, bit depth was 24, ISO speed was ISO-50, focal length was 4 mm, and max aperture was 1.69. By using a library of Python 3, namely, Pillow all images have been reshaped for the purpose of this study.

3.2 Data Augmentation

To attain satisfactory performance in deep learning, a large amount of data is needed to train CNNs. In the training stage of these networks, overfitting is a common problem. It can be defeated using data augmentation. When a CNN network fits too well with the training set, then it becomes very difficult to generalize new data by the model that was not in the training set, then overfitting happens. Details on both original and expanded black gram leaf datasets are presented in Table 2.

Rotation, cropping, flipping, shearing, zooming, and changing the brightness level of image are the most commonly used operations of data augmentation. Images are rotated clockwise by a given number of degrees from 0 to 360 in the rotation augmentation technique, 50° rotation has been used in this study. The horizontal flip and vertical flip have been used which is an extension of rotation, in which the rows or columns of pixels are reversed. The width shift and height shift have been used to make shift-invariance to the images, the range value of 0.2 has been used in both width shift and height shift. The image generation process of the expanded dataset illustrates in Fig. 2.

Table 2 Summary of black gram leaf original and expanded dataset

Dataset name	Class name	Training images	Validation images	Testing images	Total number
Original	Yellow mosaic disease	762	234	234	1230
	Healthy leaf	642	214	214	1070
	Miscellaneous	318	106	106	530
Expanded	Yellow mosaic disease	4428	1476	1476	7380
	Healthy leaf	3852	1284	1284	6420
	Miscellaneous	1908	636	636	3180

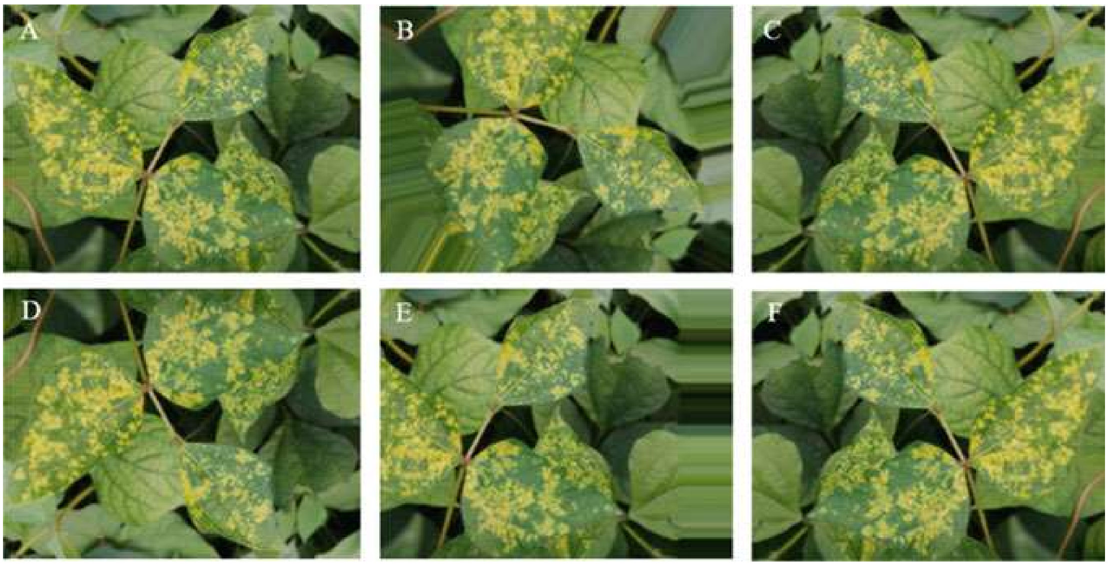

Fig. 2 Image augmentation of yellow mosaic disease image, **a** the original image, **b** rotation, **c** horizontal flip, **d** vertical flip, **e** width shift, and **f** height shift

3.3 CNN Based Models

CNNs have been used in this study to build classifiers for the yellow mosaic disease of black gram. The performance of the proposed CNN named BGCNN is compared with state-of-the-art CNN architectures such as AlexNet, VGG16, and Inception V3. The architecture of AlexNet consists of 5 convolutional layers with rectified linear unit (ReLU) activation function, 3 fully connected layers (FC), finally the Softmax layer and contains approximately 61 million parameters [15]. VGG16 contains five convolution blocks with 3×3 filters with stride 1 and same padding, maximum pooling layers that use 2×2 filters with stride 2, and three FC layers with approximately 138 million parameters [16]. To decrease the number of connections and parameters without losing the efficiency of the architecture, factorization is used in Inception V3 that consists of 42 layers. Symmetrical and asymmetrical building blocks of this architecture containing convolutions, max pooling, average pooling, concats, dropouts, and FC layers [17].

In the proposed BGCNN architecture, three convolution and maxpooling layer have been used. The convolution layer is the key element of CNNs, processes images using convolution filters. Using a set of convolution filters, the raw input image is directly applied to this layer. 3 × 3 kernel has been utilized by CNN for convolving the whole raw input image as well as the intermediate feature maps in the convolution layers. Activation functions decide whether the information received by a neuron is relevant to the given information or should be ignored. To make CNN capable of learning and performing complex tasks, these functions are applied to the input. In the proposed BGCNN architecture, ReLU has been used as it does not activate all neurons at the same time. To learn global features stacking of many convolution layers are needed, as first convolution layers extract edges, lines, corner, and other low-level features. So, three convolution layers have been used in this study. To reduce the spatial size of the representation, in CNN the pooling layer is used in between successive convolutional layers. In the network, it controls overfitting by reducing the number of parameters and computation. On the number of filters, polling has no effects [18]. By eliminating non-maximal values maxpooling layer reduces computation for upper layers. The FC layers are the last few layers in CNNs. All the features are extracted from the previous convolutional and subsampling layers are combined by this layer. In the last FC layer, the number or neurons is the same as the number of classes used to train the architecture. The size of the output layer of the proposed BGCNN is 3 as we have trained this model with three classes. As it is a multiclass classification, so the softmax activation function have been used in the FC connected layer of BGCNN which is a more generalized logistic activation. To update the weights of CNN, the loss function is used to calculate the gradients. Sparse categorical cross-entropy has been used as a loss function in this study. As an optimizer, stochastic gradient descent (SGD) has been used. SGD is performed while training [19]. The proposed BGCNN model have run for 80 epochs and have fixed 0.001 as the learning rate. Figure 3 shows the architecture of proposed BGCNN.

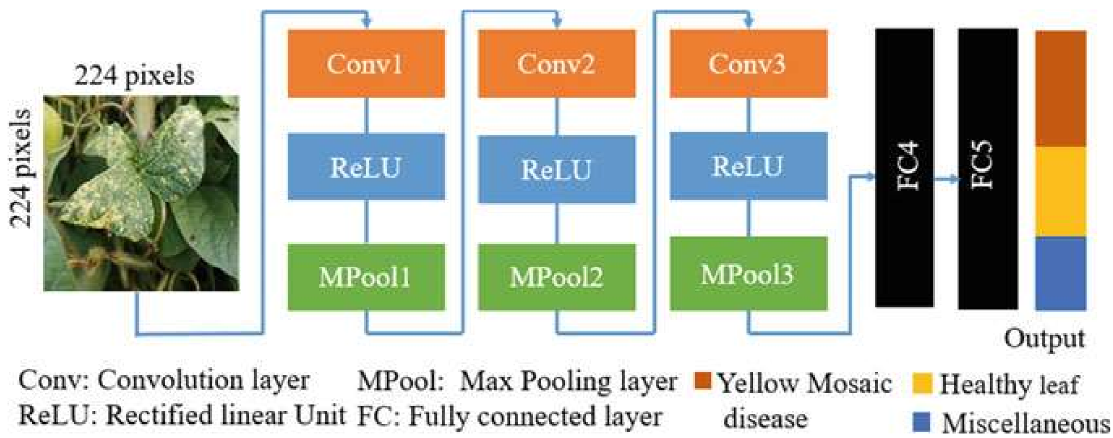

Fig. 3 Schematic representation of BGCNN

3.4 Experiments

In this study, all deep learning models have complied in Google Colab with GPU support. The multiclass classification has been performed in this study as the dataset contains three classes, yellow mosaic disease, healthy leaf, and miscellaneous. Both the original and expanded dataset of black gram leaf has been used in this study and the dataset is divided randomly into training, validation, and test sets. For training and fitting models, the training and validation sets have been used. On the other hand, the test set has been used to examine the recognition performance on images that models did not see before. With the transfer learning approach, existing CNN models have been used in this study. All the layers of these models have been set as trainable. The performance of deep learning models has been measured in this study using different metrics such as Precision (Pre), Recall (Rec), $F1$-Score ($F1$), Specificity (Spe), and Accuracy (Acc). The metrics given between Eqs. 1 and 10 are calculated using indices such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) by considering the values in the confusion matrix obtained in classifications. Here, TP is the number of total images in each class that is correctly classified by models. On the other hand, TN is the total number of correctly classified images in all classes without the relevant class. FP is the total number of misclassified images in all other classes without the relevant class, while FN represents the number of misclassified images of the relevant class. Accuracy is most commonly used to evaluate the performance of a model that is the fraction of predictions our models got right. For multi-class classification using macro-averaging, these metrics and their extended calculations are given in between Eqs. 1 and 10 [20].

For class i,

$$\mathrm{Pre}(i) = \frac{\mathrm{TP}(i)}{\mathrm{TP}(i) + \mathrm{FP}(i)} \tag{1}$$

$$\mathrm{Rec}(i) = \frac{\mathrm{TP}(i)}{\mathrm{TP}(i) + \mathrm{FN}(i)} \tag{2}$$

$$F1(i) = \frac{2 \times \mathrm{Precison} \ \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{3}$$

$$\mathrm{Spe}(i) = \frac{\mathrm{TN}(i)}{\mathrm{TN}(i) + \mathrm{FP}(i)} \tag{4}$$

$$\mathrm{Acc}(i) = \frac{\mathrm{TP}(i) + \mathrm{TN}(i)}{\mathrm{TP}(i) + \mathrm{TN}(i) + \mathrm{FP}(i) + \mathrm{FN}(i)} \tag{5}$$

$$\mathrm{AveragePre} = \frac{1}{\mathrm{classes}} \sum_{i=1}^{\mathrm{classes}} \mathrm{Pre}(i) \tag{6}$$

$$\text{AverageRe} = \frac{1}{\text{classes}} \sum_{i=1}^{\text{classes}} \text{Rec}(i) \tag{7}$$

$$\text{Average}F1 = \frac{1}{\text{classes}} \sum_{i=1}^{\text{classes}} F1(i) \tag{8}$$

$$\text{AverageSpe} = \frac{1}{\text{classes}} \sum_{i=1}^{\text{classes}} \text{Spe}(i) \tag{9}$$

$$\text{AverageAcc} = \frac{1}{\text{classes}} \sum_{i=1}^{\text{classes}} \text{Acc}(i) \tag{10}$$

4 Result and Discussion

The main aim of this study is to examine the performance of BGCNN architecture in recognizing yellow mosaic disease of black gram and to compare it with the performance of AlexNet, VGG16, and Inception V3. Both original and expanded datasets have been used for all experimental studies. Table 3 summarizes the input size, number of parameters, optimization method, and learning rate used for four models.

Classification means classifying images of the dataset to a specific class. The TP, TN, FP, FN, precision, recall, $f1$-score, and specificity values acquired by four deep learning models for each class in the expanded dataset, are presented in Table 4. Considering the precision value of four deep learning models, BGCNN has shown the best performance ranged from 94.50 to 98.31%, among pre-trained models Inception V3 has shown the best performance 96.38–97.12%. The highest recall value of 97.80% has achieved by BGCNN in the healthy leaf class. On the other hand, BGCNN and Inception V3 have achieved the highest $f1$-score of 0.97 in the healthy leaf and yellow mosaic disease class. Inception V3 has achieved the highest specificity value of 99.17% in the miscellaneous class while the highest specificity of

Table 3 The image resolutions, optimization method, learning rate, and number of parameters for deep learning models

Model name	Input size	Optimization method	Learning rate	Number of total parameters
AlexNet	227 × 227	Adam	0.001	25,723,471
VGG16	224 × 224	SGD	0.01	134,272,835
Inception V3	299 × 299	Adam	0.001	21,808,931
BGCNN	224 × 224	SGD	0.001	3,240,163

Table 4 Class wise classification performance of deep learning models

Model name	Class	TP	TN	FP	FN	Pre (%)	Re (%)	$F1$ (%)	Spe (%)
AlexNet	Y	1373	1864	103	56	93.02	96.08	0.95	94.76
	H	1216	2004	68	108	94.70	91.84	0.93	96.72
	M	596	2713	40	47	93.71	92.69	0.93	98.55
VGG 16	Y	1402	1878	74	42	94.99	97.09	0.96	96.21
	H	1234	2041	50	71	96.11	94.56	0.95	97.61
	M	607	2720	29	40	95.44	93.82	0.95	98.95
Inception V3	Y	1423	1881	53	39	96.41	97.33	**0.97**	97.26
	H	1247	2066	37	46	97.12	96.44	**0.97**	98.24
	M	613	2732	23	28	96.38	95.63	0.96	**99.17**
BGCNN	Y	1451	1867	25	53	**98.31**	96.48	**0.97**	98.68
	H	1246	2084	38	28	97.04	**97.80**	**0.97**	98.21
	M	601	2743	35	17	94.50	97.25	0.96	98.74

(Y) Yellow mosaic disease, (H) healthy leaf, and (M) miscellaneous
Bold value indicates highest value of performance metrics obtained by the model

the yellow mosaic disease class has achieved by BGCNN. For the yellow mosaic disease class, BGCNN has been achieved precision the highest precision, 98.31%, and Inception V3 has the highest precision for both healthy leaf and miscellaneous class, 97.12%, and 96.38%, respectively.

On the expanded dataset, the average precision, recall, $f1$-score, specificity, and accuracy values obtained by four deep learning models are given in Table 5. In the training phase of all deep learning models, 80 epochs have been used. By dividing the total training time of each model by 80, the time per epoch has been calculated and presented in Table 5. Inception V3 has achieved the highest true classification rate of the samples that the model classifies as positive (precision). On average recall, BGCNN has performed better than other models. Inception V3 and BGCNN has achieved the highest average $f1$-score. The training of inception V3 has taken more

Table 5 Average results of deep learning models

Model name	Average-Pre (%)	Average-Re (%)	Average-$F1$	Average-Spe (%)	Average-Acc (%)	Time per epoch (s)
AlexNet	93.81	93.53	0.94	96.67	95.86	351
VGG16	95.51	95.15	0.95	97.59	96.99	1183
Inception V3	**96.63**	96.46	**0.97**	98.22	97.78	1904
BGCNN	96.61	**97.17**	**0.97**	**98.54**	**98.07**	**283**

Bold value indicates highest value of performance metrics obtained by the model time than others, completed in 42 h 19 min. BGCNN has achieved highest average specificity, accuracy with the lowest training time per epoch.

A comparative experiment was introduced in this section to examine the effect of data augmentation on classification accuracy. Figure 4 shows a remarkable change in test accuracy of all deep learning models after using the expanded dataset of black gram. Test accuracy of BGCNN using the original dataset is 82.67% while using the expanded dataset it has achieved 97.11% test accuracy. Inception V3 has performed better than other pre-trained deep learning models using the original dataset. On the other hand, BGCNN has achieved the highest test accuracy with the expanded dataset. Using the original dataset, AlexNet, VGG16, and Inception V3 have achieved recognition accuracy of 71.14%, 76.35%, and 79.24%, respectively. On the other hand, AlexNet, VGG16, and Inception V3 have achieved 93.78%, 95.49%, and 96.67%, respectively, recognition accuracy with the expanded dataset of black gram. The outcome of this experiment demonstrates that models trained with the expanded dataset can learn more suitable features, under various environments it enhances the anti-interference performance.

To illustrate the performance of deep learning models with expanded datasets more perceptibly, the total number of incorrect classifications for each class was given in Table 6. One remarkable performance has been performed by BGCNN for the yellow mosaic disease class. On the other hand, the lowest number of misclassifications has been performed by Inception V3 for the miscellaneous class.

In this study, a new CNN model has developed from scratch which achieved 86.06% training accuracy and 82.67% test accuracy using the original dataset, after

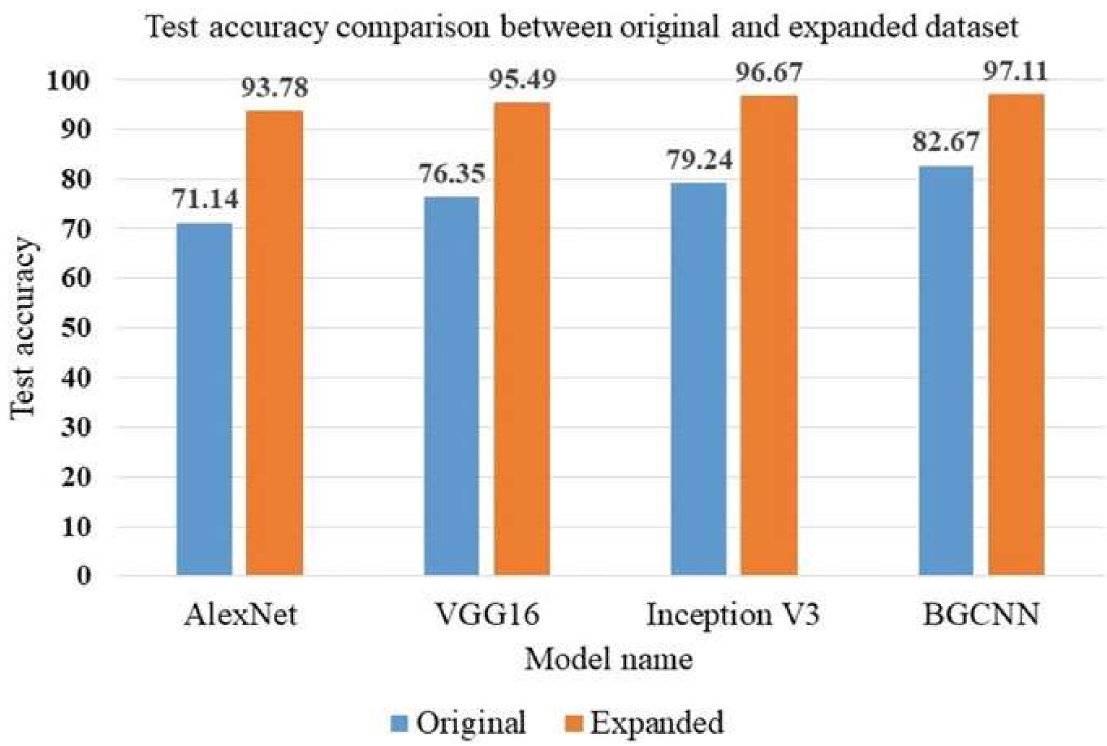

Fig. 4 Test accuracies for deep learning models on both original and expanded datasets

Table 6 Misclassification numbers of deep learning models for each class

Class name	AlexNet	VGG16	Inception V3	BGCNN
Yellow mosaic disease	103	74	53	25
Healthy leaf	68	50	37	38
Miscellaneous	40	29	**23**	35
Total false predictions for expanded dataset	211	153	113	98

Bold value indicates highest value of performance metrics obtained by the model

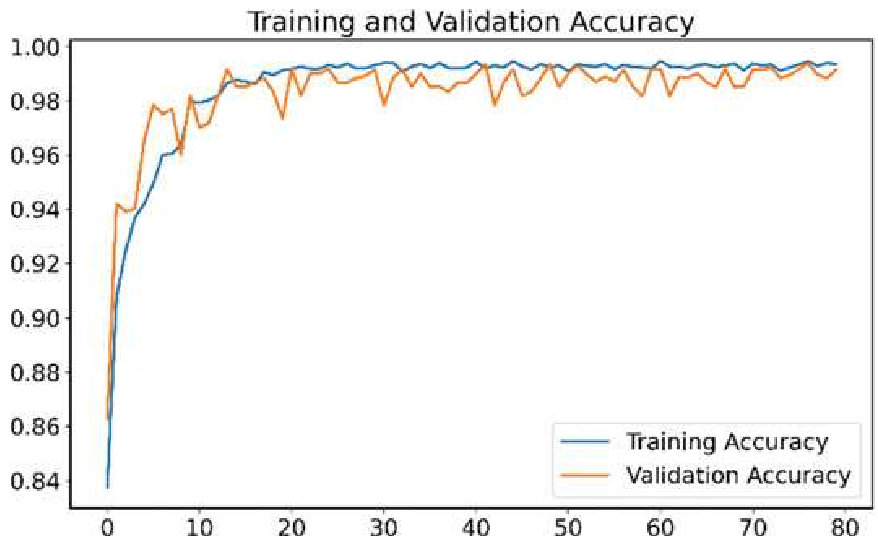

Fig. 5 Training and validation accuracy curve of BGCNN for expanded dataset

using the expanded dataset it has shown superior recognition performance, training accuracy increased to 97.81%, and test accuracy increased to 97.11%. Accuracy and loss curve of both training and validation of BGCNN with expanded dataset are shown in Figs. 5 and 6. The other three pre-trained models have also performed better with the expanded dataset, among these Inception V3 has performed better than others.

State-of-the-art CNN models need more training time and contain a large number of layers and parameters compare to BGCNN. These models have taken more time than BGCNN during the prediction of unknown images.

5 Conclusion

This paper has proposed a deep learning architecture to recognize the yellow mosaic disease of black gram, namely, BGCNN. Using image augmentation 16,980 images have been created based on 2830 images of black gram leaves. The performance of BGCNN has also compared with the state-of-the-art deep learning architectures used in leaf disease recognition in the literature. The success of BGCNN has significantly

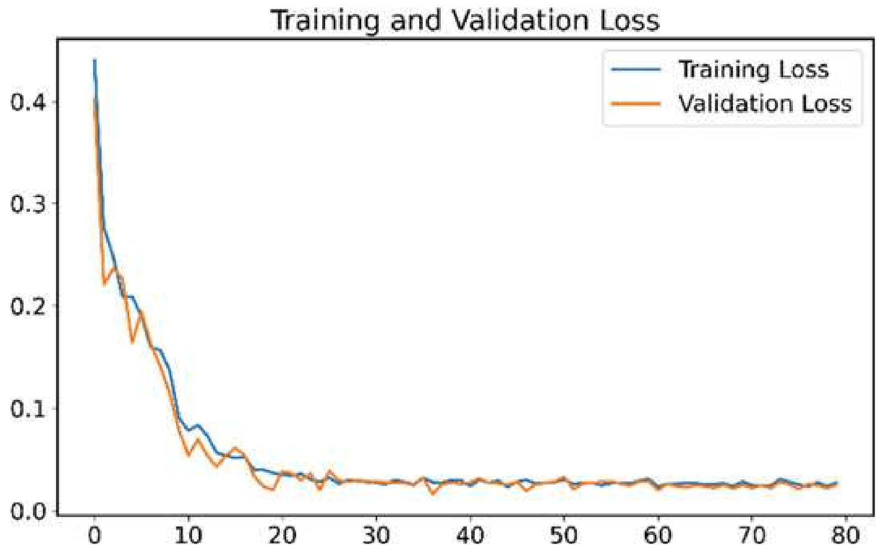

Fig. 6 Training and validation loss curve of BGCNN for expanded dataset

changed after using the expanded dataset. The BGCNN model has achieved 82.67% test accuracy with the original dataset, while BGCNN with the expanded dataset has achieved 97.11%. Besides, this study also illustrates the advantage of using pre-trained models, especially if the training dataset is not large. On the other hand, when the training time of models analyzed, BGCNN had taken the lowest time with 80 epochs in both the original and expanded dataset. This study aimed to develop a recognition approach for rapid and accurate diagnosis of yellow mosaic disease, our model is unable to recognize other diseases of black gram which is a limitation of this work. In feature works, it is planned to expand the black gram leaf disease dataset and the number of classes.

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