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Conference Paper · July 2022

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Recognition of Mustard Plant Diseases Based on Improved Deep Convolutional Neural Networks

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***Abstract*—Diseases of the mustard plant are a major threat to the quality production of mustard oil, but rapid recognition of these diseases becomes cumbersome due to the absence of expert identification infrastructures. This study introduced an improved diagnosis method for diseases of the mustard plant using deep convolutional neural networks (CNNs) to ensure sustainable improvement in mustard farming. First, the mustard plant dataset of nine classes is built using eleven image augmentation techniques that contain 47760 images of leaf, stem, and pod. Afterward, a CNN architecture, namely, MPNet, is designed and trained from scratch in this study that consists of deep separable convolutional layers and inception modules, which realize 97.11% accuracy in recognizing 2388 test images. The recognition performance of MPNet is also compared with four state-of-the-art CNNs, where MobileNetV2 acquired 92.83% test accuracy. The results authenticate that the proposed MPNet can competently recognize diseases of the mustard plant.**

Keywords—Deep Learning, Convolutional Neural Networks, Transfer Learning, Deep Separable Convolution, Inception, Mustard Plant Disease, Smart Agriculture

I. INTRODUCTION

Mustard oil is widely used for cooking in Bangladesh, India, and Nepal, which is made from seeds of the mustard plant (binomial name: *Brassica nigra*). The cultivation of mustard plants is one of the most profitable farming for its high market and economic value [1]. However, different types of diseases occur repeatedly during mustard plant farming, which causes substantial financial losses. For sustainable development in agriculture, accurate and early recognition of diseases of the mustard plant is of high importance, as well as for minimizing financial losses and reducing the use of pesticides. In recent years, disease recognition of several crops using deep learning approaches has become a research hotspot in modern agriculture to enhance production [3].

In mustard plant farming, visual recognition is utilized for disease identification due to the absence of automated approaches, which is a highly laborious and time-consuming task. In computer vision, CNNs are now widely applied for image classification, which significantly improved the recognition ability of automated identification approaches. In traditional machine learning (ML) approaches, complex image processing is required for extracting features from images, which is an extremely troublesome task [7] [12]. On the other hand, CNNs automatically extract features from images and also provide remarkably higher accuracy than ML approaches. CNNs are crucial for the efficient identification of crop diseases, and also demonstrated significant performance in classifying crop diseases recently in different studies. Pre-trained CNNs are also extensively used in several studies for classifying crop diseases.

White rust, leaf spot, blackleg, fusarium wilt, stem rot, and pod spot are the six common types of diseases of mustard plants, which intensely affect the yield of mustard plants [2]. By performing eleven different image augmentation techniques (IAT), a total of 45372 images were generated. IAT helps to reduce the overfitting phenomenon of CNNs by creating sufficient images for the learning of CNNs [14]. All images were randomly divided into training, validation, and testing images after performing IAT, where the training, validation, and testing set contains 38211, 7161, and 2388 images, respectively. The distinctions among disease symptoms significantly contribute to the efficient recognition of different mustard plant diseases. Motivated by the recent breakthroughs of CNNs in identifying crop diseases, an efficient recognition model is addressed in this study, which is based on an improved CNN architecture that is designed using deep separable convolutional layers (DSCL) and inception modules (IM). DSCL requires less computing resources than the traditional convolutions but provides a higher speed of training, and also reduces overfitting by decreasing parameters [14]. On the other hand, IM uses parallel layers of several convolutions, which helps a network in extracting features efficiently with less overfitting and consumption of computing resources. Moreover, the recognition performance of the addressed network, namely, Mustard Plant Network (MPNet), was compared with four pre-trained models, which were utilized using the transfer learning approach on the mustard plant dataset. In this study, the MPNet model acquired 97.11% accuracy, where MobileNetV2, DenseNet121, VGG19, and ResNet50 obtained 92.83%, 91.37%, 90.24%, and 88.02% accuracy on the test images of the mustard plant dataset. MPNet exhibited significant robustness and recognition performance than pre-trained models in several experimental studies, which strongly illustrates that the addressed model can effectively recognize diseases of mustard plants. The major contributions of this study are summarized as follows:

- The mustard plant dataset is generated for providing significant generalization ability to the addressed CNN architecture. All images were collected from several mustard plant fields with intricate and identical backgrounds. IAT is used in this dataset for increasing robustness and preventing the overfitting of CNNs during the training phase.

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- For efficient diagnosis of mustard plant diseases, MPNet is addressed in this study, which was designed using DSCL and IM. MPNet acquired 97.11% recognition accuracy which was higher than state-of-the-art CNNs, which indicates the effective identification capability of MPNet firmly. To the best of our knowledge, this is the first study that was conducted for mustard plant diseases recognition.

The rest of this study is structured as follows: Section II describes related studies. Section III provides details of the mustard plant dataset and CNNs utilized in this study. The results obtained in this study are provided and demonstrated in Section IV. Finally, this paper is concluded in Section V.

II. Related Work

In recent years, plant disease recognition by utilizing ML algorithms and CNNs has become an active research topic for ensuring sustainability in agriculture. Yan et al. addressed an identification algorithm for plant disease using deep learning, which obtained 83.57% accuracy, and the Chan-Vese algorithm is utilized for segmenting images [3]. The recognition efficiency of their introduced algorithm is also compared with the ResNet101 model which acquired 42.50% accuracy. Mohammad et al. proposed AlexNet for extracting features from images and support vector machine (SVM) for the classification of maize leaf disease and acquired 95.00% accuracy [4]. On the other hand, AlexNet acquired 93.30% and 73.30% accuracy with k-Nearest neighbor (KNN), and decision tree (DT), respectively. Besides AlexNet, VGG16, VGG19, GoogleNet, InceptionV3, ResNet50, and ResNet101 were also used for feature extraction. SVM, kNN, and DT acquired 88.33%, 82.37%, and 74.51% average accuracy. Sameerchand et al. introduced a recognition approach using CNN for classifying seventy medicinal plants through a mobile application and acquired 90.00% accuracy [5]. Vimal et al. addressed a recognition method for rice plant disease using CNN and SVM and obtained 91.37% accuracy [6]. AlexNet was utilized for extracting features and SVM was used for performing classification. Three different training-testing partitions such as 60%-40%, 70%-30%, and 80%-20% were used, and acquired 89.45%, 90.39%, and 91.37% accuracy, respectively. For classifying rice leaf diseases, Muhammad et al. proposed XGBoost which acquired 86.58% accuracy [7]. By using hue threshold, affected portions were segmented and statistical features include color, shape, and texture were extracted from images. On the other hand, SVM obtained 81.67% accuracy with the radial basis function, and 82.00% F1-Score, where XGBoost acquired 87.00% F1-Score. Debasish et al. introduced a detection method using SVM for leaf disease, which obtained 87.60% accuracy [8]. The detection performance of SVM was also compared with logistic regression (LR) and random forest (RF), where LR and RF acquired 67.30% and 70.05% accuracy, respectively. Trang et al. addressed an identification approach for mango diseases using CNN that acquired 88.46% accuracy where three pre-trained CNNs include InceptionV3, AlexNet, and MobileNetV2 obtained 78.48%, 76.92%, and 84.62% accuracy [9]. For enhancing the quality of images rescaling, and center alignment were used, and the golden section search technique was utilized to enhance the contrast. Fenu et al. addressed a multioutput learning method for diagnosing diseases of plant and severity of stress, and five pre-trained CNNs include VGG16, VGG19, ResNet50, InceptionV3, MobileNetV2, and EfficientNetB0 were used [10]. InceptionV3 performed better than others in diagnosing biotic stress that obtained 90.68% accuracy, where EfficientNetB0 performed better than others in diagnosing severity which acquired 78.31% accuracy. The training time of CNNs was also analyzed, and EfficientNetB0 consumed less training time than others. Zaki et al. introduced a classification method for diseases of tomato leaves using MobileNetV2 and acquired 95.94% accuracy with a batch size of 16 [11]. The performance of five optimization methods, three learning rates, and four training and testing image ratios was analyzed where the Adagrad optimization method, the learning rate of 0.0001, and the training and test image ratio of 4:1 performed better than others. Kamal et al. introduced a classification method using SVM for leaf diseases of oil palm that acquired 97.00% and 95.00% accuracy in classifying chimaera and anthracnose leaf disease and utilized k-means clustering to segment images [12]. Leong et al. introduced an identification method using SVM for diseases of plant leaf that obtained 96.63% accuracy, and in segmenting images, the color thresholding approach performed better than the k-means clustering technique [13]. The gray-level co-occurrence matrix (GLCM) and ResNet50 were utilized to extract features from images where ResNet50 performed better than GCLM.

In the above-mentioned research works, CNNs especially pre-trained models showed significant recognition efficiency over ML algorithms. But, CNNs is rarely utilized for mustard plant diseases recognition. Hence, an improved CNN is addressed in this research work for the efficient diagnosis of mustard plant diseases.

III. Materials And Methods

A. The Mustard Plant Dataset

A field dataset of 2388 images of mustard plants leaf, stem, and pod was collected initially, which includes nine classes, and Fig. 1 shows the example image of nine classes with labels.

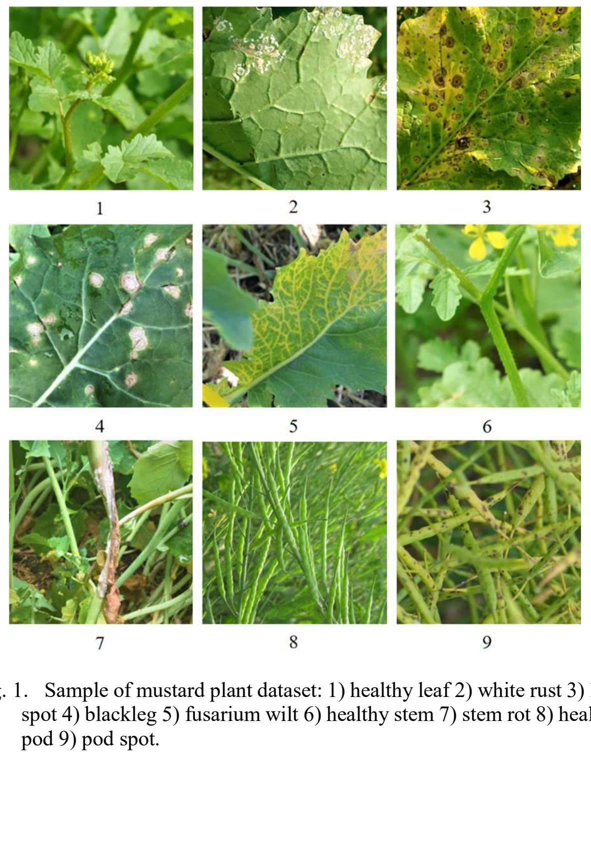

Fig. 1. Sample of mustard plant dataset: 1) healthy leaf 2) white rust 3) leaf spot 4) blackleg 5) fusarium wilt 6) healthy stem 7) stem rot 8) healthy pod 9) pod spot.

All raw images of this dataset were resized to 224×224 pixels and were inconstantly divided into training, validation, and test images by 85%, 15%, and 5%, respectively. Moreover, IAT was utilized in this study for simulating interference of real-life to eradicate the overfitting issue, and IAT enhances the efficiency of CNNs significantly. With more generated images via IAT, CNNs can learn several patterns, and achieve better recognition performance. Eleven IAT was applied to collect images for increasing the diversity and quantity of mustard plant images in this study, where six was color IAT and five was position IAT, and Fig. 2 represents examples of eleven used IAT.

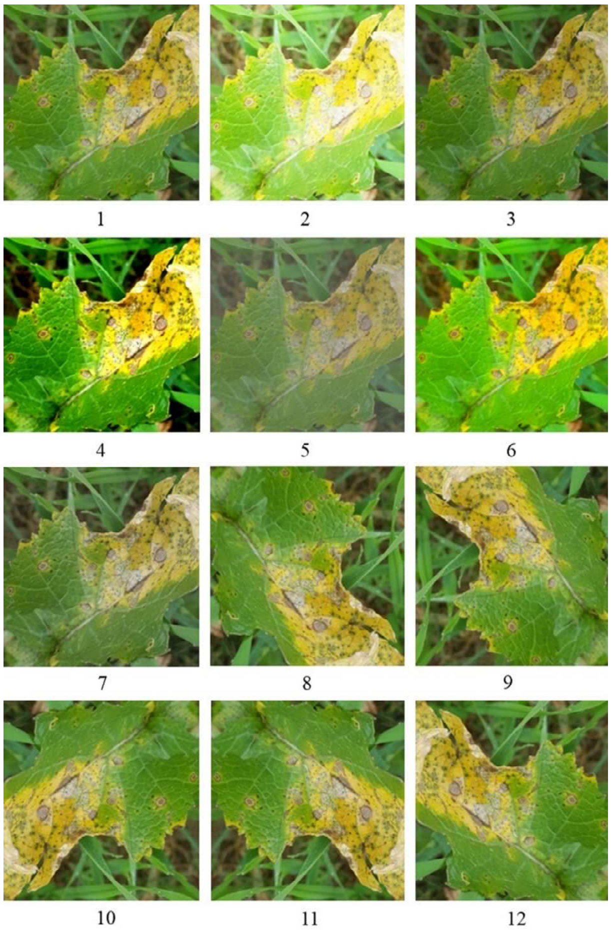

Fig. 2. IAT of mustard plant images: 1) original image, 2) high brightness, 3) low brightness, 4) high contrast, 5) low contrast, 6) high saturation, 7) low saturation, 8) 90-degree rotation, 9) 270-degree rotation, 10) 180-degree rotation, 11) vertical symmetry, 12) horizontal symmetry.

B. *MPNet*

CNNs brought a crucial breakthrough in deep learning-based computer vision techniques of image recognition, which is now widely used in several studies for ensuring the sustainability of agriculture. An enhanced CNN, namely, MPNet, is designed from scratch for efficient recognition of nine classes of mustard plant dataset, which was built using DSCL, and IM. DSCL and IM were the key layers of this architecture, which were used for enhancing the performance of MPNet. Besides DSCL, and IM, max-pooling (MP), batch normalization (BN), global average pooling, and softmax were also used in MPNet architecture.

CNNs built with DSCL require fewer parameters than normal convolution layers, which also enhances the generalization performance of CNNs. DSCL consists of depthwise and pointwise convolution, which requires less computing resources than normal convolution layers. DSCL helps CNNs to reduce overfitting issues without reducing the performance of the model. The structural design of MPNet is demonstrated in Fig. 3.

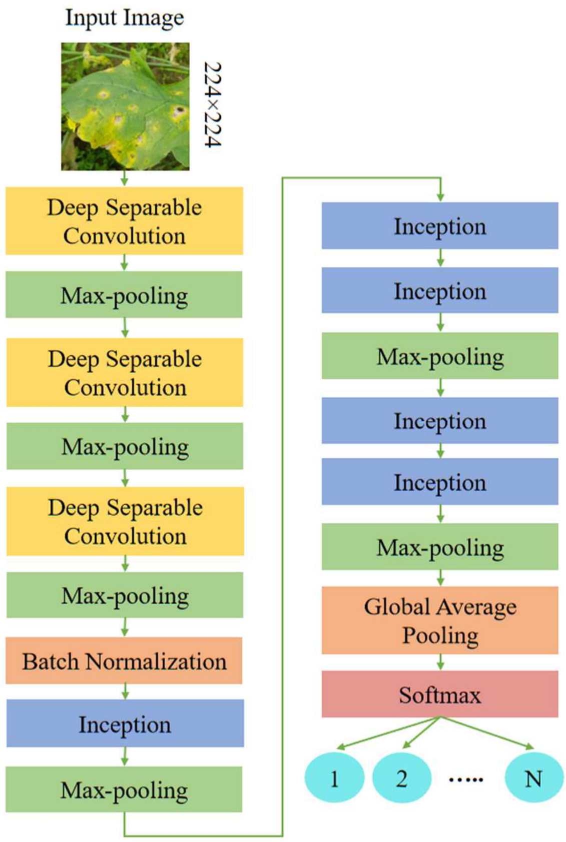

Fig. 3. Structure diagram of the addressed MPNet.

In MPNet architecture, the first DSCL contains 64 convolution kernels (CK) of size 3×3 and a 3×3 MP layer was added after it. MP layer selects the maximum value covered by the filter from the region of each feature map. The second DSCL contains 64 CK of size 3×3, and a 3×3 MP layer was added after it. The last DSCL contains 128 CK of size 3×3, which was followed by a 3×3 MP and a BN layer. BN makes CNNs more stable and faster, which normalized elements of a layer to zero mean and unit variance. Afterward, a IM was added which was followed by a 3×3 MP layer. And then two IM was added which was followed by a 3×3 MP layer. Again, two IM was added which was followed by a 3×3 MP layer. For improving the feature extraction ability of CNN's, the depth or width of the model is needed to be increased, which increases overfitting and consumption of computing resources. On the other hand, IM extracts features efficiently by utilizing parallel layers of several convolution kernel sizes, and outputs of these are concatenated at the end of the model, which remarkably improves the adaptability of the network. As demonstrated in Fig. 4, IM was designed with collateral 1×1 convolution layers (CL), 3×3 CL, and two cascaded 3×3 CL which were alongside a MP layer. Moreover, a 1×1 CL was added before or after the collateral CL for decreasing the dimensions of the feature map and weights numbers. The global average pooling layer is connected to a nine-way softmax layer in MPNet, and adaptive moment estimation

(Adam) was chosen as an optimization algorithm for MPNet. The structure of the used IM is demonstrated in Fig. 4.

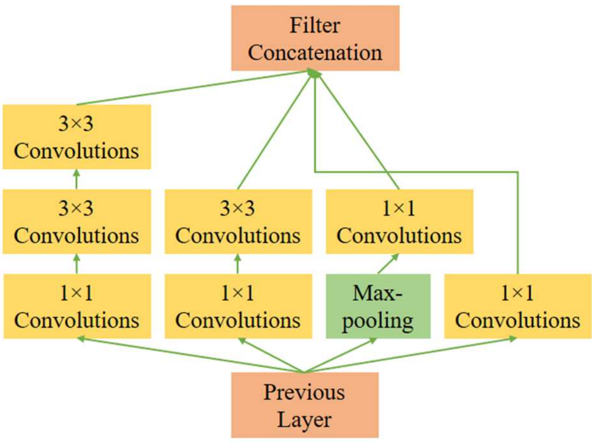

Fig. 4. Inception structure with convolution kernels size.

C. *State of the art CNN models*

In the transfer learning strategy, state-of-the-art CNN models are used for building efficient CNNs, which were been already trained on a large-scale dataset. In this study, four CNNs such as MobileNetV2, DenseNet121, VGG19, and ResNet50 were utilized via the transfer learning strategy, and the input image size of these four CNNs are the same which is 224×224 pixels. Initially, convolutional bases (CB) of these pre-trained models were set unfrozen, and fully connected (FC) layers were replaced for performing classification on the mustard plant dataset. Afterward, CB and FC layers were retrained. In fine-tuning of CNNs, basic CNNs were utilized as feature extractors, where input images were propagated. Afterward, a global average pooling layer was used for generating a one-dimensional matrix from extracted feature maps. A fully FC layer was used with 128 neurons, and for eradicating the overfitting issue a dropout layer of coefficient of 0.5 was added. Then a FC layer of 64 neurons and a dropout layer of 0.5 were used. Lastly, the final FC layer was connected to a nine-way softmax layer for classifying nine classes of the mustard plant dataset. The fine-tuning strategy is illustrated in Fig. 5.

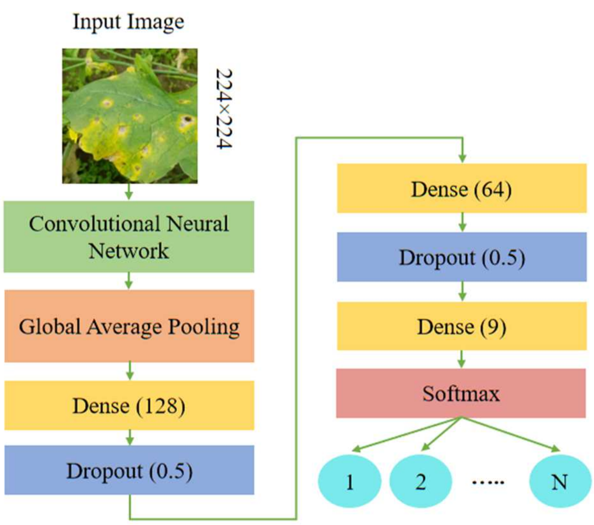

Fig. 5. The used fine-tuning strategy.

IV. EXPERIMENTS

All experiments introduced in this study were conducted using the Google cloud environment, and for implementing the MPNet model, Keras 2.4.0 framework was used. During the training stage of MPNet and four pre-trained CNNs, 38211 training and 7161 validation images were used. For evaluating the recognition efficiency of five CNNs, several experimental studies were conducted using 2388 test images of the used dataset. Four pre-trained CNNs such as MobileNetV2, DenseNet121, VGG19, and ResNet50 were utilized with the same method of optimization as utilized during the training phase on the ImageNet dataset. In the training phase of CNNs, the early stopping technique (EST) was utilized, and categorical cross-entropy was utilized as a loss function for eliminating the overfitting problem and monitoring generalization error.

The recognition efficiency of the five modes on the test of the mustard plant dataset was validated using four analytics metrics include sensitivity (Sen), specificity (Spe), accuracy (Acc), and precision (Pre) which were attained from the number of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) [14]. The mathematical formulas of analytics metrics are given in equations (1) to (4).

For a class *mi*,

$$Sen(mi) = \frac{TP(mi)}{TP(mi) + FN(mi)} \tag{1}$$

$$Spe(mi) = \frac{TN(mi)}{TN(mi) + FP(mi)} \tag{2}$$

$$Acc(mi) = \frac{TP(mi) + TN(mi)}{TP(mi) + TN(mi) + FP(mi) + FN(mi)} \tag{3}$$

$$Pre(mi) = \frac{TP(mi)}{TP(mi) + FP(mi)} \tag{4}$$

V. RESULTS AND DISCUSSIONS

This study addresses an improved recognition approach for mustard plant diseases using MPNet architecture for achieving a good equipoise between the recognition accuracy and time. DSCL and IM improved the recognition efficiency of MPNet architecture significantly, which performed better than pre-trained CNNs, such as MobileNetV2, DenseNet121, VGG19, and ResNet50. MPNet acquired 97.56% and 96.09% training and validation accuracy, respectively, which wrongly classified 69 test images. Training, validation and test accuracy of CNNs are presented in Table 1. MobileNetV2 misclassified 171 test images, which outperforms four pre-trained CNNs in recognition efficiency.

TABLE I. RECOGNITION ACCURACY OF CNN MODELS

Model Name	Training Accuracy	Validation Accuracy	Test Accuracy
MPNet	**97.56%**	**96.09%**	**97.11%**
MobileNetV2	93.58%	90.57%	92.83%
DenseNet121	91.89%	89.35%	91.37%
VGG19	91.34%	88.13%	90.24%
ResNet50	89.13%	87.85%	88.02%

MobileNetV2 obtained 92.83% test accuracy, whereas ResNet50 acquired 88.02% test accuracy which was the lowest test accuracy among pre-trained models. The recognition efficiency of pre-trained CNNs was very close to each other. DenseNet121, VGG19, and ResNet50 wrongly classified 206, 233, and 286 images of the test set, respectively. The normalized confusion matrix of MPNet for the test set is presented below in Fig. 6, which strongly demonstrates the competency of this architecture.

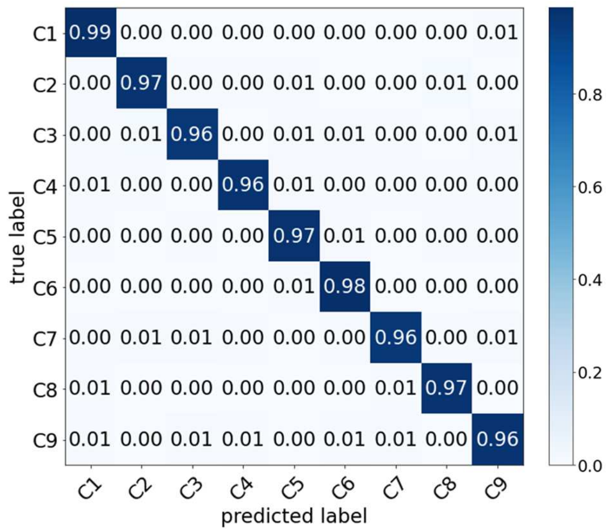

Fig. 6. Normalized confusion matrix of MPNet architecture: C1) healthy leaf, C2) white rust, C3) leaf spot, C4) Blackleg, C5) fusarium wilt, C6) healthy Stem, C7) stem rot, C8) healthy pod and C9) pod spot.

According to class-wise recognition performance, MPNet delivered a satisfactory performance, which is presented in Table 2. The sensitivity of the Blackleg class was higher than others, 98.02%. In the Pod spot class, MPNet acquired 95.00% sensitivity which was less than other classes. However, MPNet obtained 99.76% specificity in the Healthy Stem class. Accuracy of white rust, blackleg, healthy stem, and healthy pod class was the same, 99.41%. MPNet acquired the lowest accuracy in the Leaf spot class, 99.20%. Moreover, the precision of the healthy leaf class was higher than other classes, 98.71%. In the leaf spot class, MPNet obtained the lowest precision value, 95.53%. The precision value of white rust, blackleg, healthy stem, and healthy pod classes is 96.60%, 96.48%, 98.48%, and 97.14% respectively, where MPNet obtained the highest accuracy.

TABLE II. CLASS-WISE RECOGNITION PERFORMANCE OF MPNET

Class name	Sen (%)	Spe (%)	Acc (%)	Pre (%)
Healthy leaf	97.45	99.75	99.37	**98.71**
White rust	97.42	99.63	**99.41**	96.60
Leaf spot	96.71	99.49	99.20	95.53
Blackleg	**98.02**	99.58	**99.41**	96.48
Fusarium wilt	96.12	99.72	99.37	97.38
Healthy Stem	97.31	**99.76**	**99.41**	98.48
Stem rot	97.32	99.54	99.33	95.61
Healthy pod	97.84	99.62	**99.41**	97.14
Pod spot	95.00	99.68	99.29	96.45

Symptoms of diseases are very analogous in respect of geometrical features and CNNs may misjudge during fine-grained recognition. Based on DSCL and IM, MPNet efficiently extracted disease features from images, which remarkably increased the accuracy of image classification. In healthy leaf and healthy stem classes, MPNet wrongly predicted 5 images, which was the lowest false prediction number of this study. Images of healthy leaf and healthy stem classes were less complex with no disease spots, which significantly increased the recognition accuracy of MPNet for these two classes. Images of the leaf spot class were very complex, containing rounded disease spots with the yellow surface, which decreased MPNet accuracy for this class. On the other hand, MobileNetV2 falsely predicted 26 images of the healthy pod class, which was higher than other classes. DenseNet121 misclassified 29 images of the healthy pod and 14 images of the blackleg class. VGG19 wrongly classified 32 images of the leaf spot, which was higher than other classes. However, VGG19 misclassified 18 images of the stem rot class, which was less than other classes. Lastly, ResNet50 misclassified 39 images of the fusarium wilt and healthy pod class, which was the highest misclassification number of this study. Supported by the results of several experiments, MPNet architecture obtains superior recognition performance in classifying images of nine classes. Class-wise false classification numbers are presented in Table 3. At the end of 53 epochs, the loss of MPNet architecture was remarkably reduced and yielded the highest accuracy, where no major fluctuations were found in the curve of accuracy and loss. The accuracy curve acquired for MPNet architecture on the training and validation sets is given in Fig. 7.

TABLE III. FALSE CLASS-WISE CLASSIFICATION NUMBERS OF CNNS

Class name	MP Net	Mobile NetV2	Dense Net121	VGG 19	ResNet 50
Healthy leaf	**5**	18	26	28	36
White rust	8	24	23	23	38
Leaf spot	11	15	27	32	**22**
Blackleg	9	20	**14**	26	23
Fusarium wilt	6	21	18	22	39
Healthy Stem	**5**	17	28	31	26
Stem rot	10	18	24	**18**	35
Healthy pod	8	26	29	27	39
Pod spot	7	**12**	17	26	28

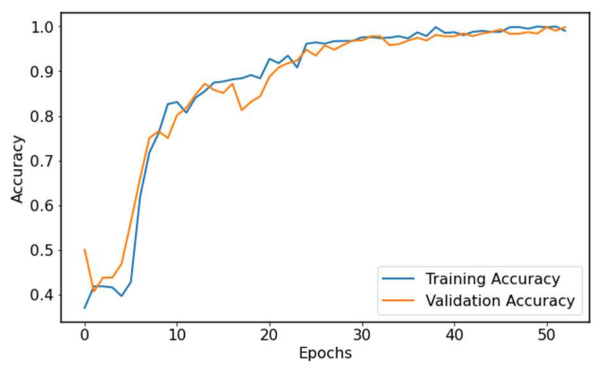

Fig. 7. Learning accuracy curves of MPNet architecture.

During the training process of CNNs, epoch number was not set previously as EST was used for finding the optimal number of epochs. Four CNNs including MobileNetV2, DenseNet121, VGG19, and ResNet50 delivered their highest recognition performance after 49, 56, 58, and 53 epochs. The loss curve obtained for MPNet architecture on the training and validation sets is given in Fig. 8.

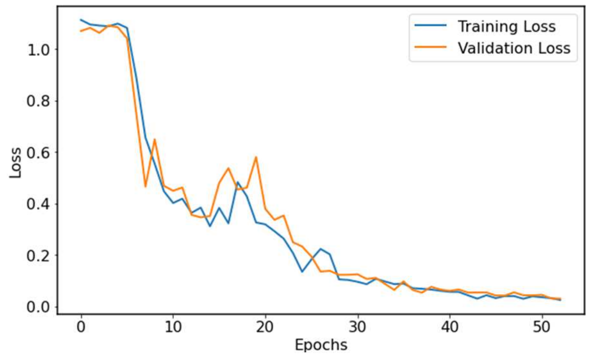

Fig. 8. Learning loss curves of MPNet architecture.

The proposed MPNet architecture's performance was compared in this study with the existing literature which were addressed for diagnosing diseases of other crops, presented in Table 4. The comparison study presented in Table 4 validates that the introduced architecture demonstrates superior performance compared to existing studies.

TABLE IV. COMPARISON OF MPNET ARCHITECTURE WITH METHODS OF EXISTING LITERATURE

Study	Method	Classes	Accuracy
Yan et al. [3]	CNN	4	83.57%
Mohammad et al. [4]	AlexNet, SVM	4	95.00%
Vimal et al. [6]	AlexNet, SVM	4	91.37%
Muhammad et al. [7]	XGBoost	3	86.58%
Debasish et al. [8]	SVM	7	87.60%
Fenu et al. [10]	InceptionV3	4	90.68%
Zaki et al. [11]	MobileNetV2	4	95.94%
Kamal et al. [12]	SVM	2	90.00%
Leong et al. [13]	ResNet50, SVM	4	96.63%
Our study	**MPNet**	**9**	**97.11%**

VI. CONCLUSION

To this day, the cultivation of several types of crops remains highly crucial, which also plays an appreciable role in the economy of most countries and also in our everyday life. This paper presented an improved CNN architecture using DSCL and IM for mustard plant diseases, and MPNet obtained 97.11% accuracy in recognizing images of nine classes. The mustard plant dataset containing 47760 images was generated in this study by utilizing 11 IAT for ensuring adequate generalization performance of CNNs. In MPNet architecture, IM enhanced accuracy by strengthening the multidimensional feature extraction ability of MPNet, and global average pooling was utilized instead of the FC layer for decreasing the parameters number of the model. The recognition performance of four pre-trained CNNs was also evaluated on the same dataset, where MobileNetV2 outperformed other CNNs that attained 92.83% accuracy. Specifically, the efficiency of recognition of the addressed architecture in each class firmly confirmed the robustness of MPNet. The experimental results on the mustard plant dataset indicated that MPNet architecture is effective and feasible. As future works, expanding the dataset, collecting new samples, and adding other classes of the mustard plant is an aim of this research work.

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