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Original Article

Deep Learning Based Tomato PLDD

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Abstract *- Agriculture sector is the prime source of food and industrial raw material that satisfies the increasing population demand and industrial revolution. However, plant leaf disease detection (PLDD) degrades the quality of food and agricultural products, leading to economic loss for farmers. Recently, many deep learning frameworks have been presented for the PLDD that has shown gigantic improvement over traditional machine learning-based leaf disease detection. The performance of these deep learning frameworks is often limited due to lower feature variability, data scarcity problem, and low accuracy for multiple plant disease detection. This article presents PLDD based on a deep convolutional neural network (DCNN) to improve the feature variability and disease detection accuracy. The effectiveness of the proposed approach is evaluated on tomato plants from the PlantVillage dataset. The proposed method provides 98.83% and 96.06% accuracy in 2-class and 9-class for PLDD.*

Keywords *- Agricultural Automation, PLDD, Deep Learning, Precision Agriculture, Convolutional Neural Network.*

1. Introduction

Tremendous global population growth leads to a huge demand for food sources and industrial raw materials. The agriculture sector is the prominent source of food and industrial raw material. The economic and social growth of developing countries like India, China, Indonesia, etc., hugely depends upon the growth of the agriculture sector [1-2]. Also, the agriculture sector is the prime source of employment. However, plant disease caused due to adverse climate conditions, less or excess water, pest, viruses, and insects decreases the quality of food and agricultural products [3-5]. Manual disease detection is tedious and inefficient because of various factors such as being prone to error, less accurate due to inadequate knowledge of expert/farmer, less understanding due to vision problems, etc. The leaves of the plants show the disease symptoms reflected in leaf color variation, texture variation, spots on the leaf surface, and damage to the leaf. Various automatic computer vision-based techniques are used for PLDD using ML and DL [6-10].

The CNN-based deep learning architectures are widely accepted for many computer vision-based applications. Various deep and transfer learning-based PLDD systems have been presented in the past few years. Mohanty et al. [11] investigated GoogleNet and AlexNet for disease detection of 28 classes, resulting in an accuracy of 99.34% and 99.27%, respectively. Sladojevic et al. [12] explored fine-tuned CNN framework for PLDD of 13 plants, giving an accuracy of 96.30%. Ramcharan et al. [13] proposed transfer learning based on GoogleNet (InceptionV3) for paste damage and disease detection in cassava plants. Further, Funtes et al. [14] developed faster R-CNN for PLDD, resulting in 83% accuracy. Ferentinas et al. [15] explored various DL frameworks for PLDD, such as AlexNetOWTBn and VGG. It provided 99.53% and 99.49% accuracy for 58 diseases for VGG and AlexNetOWTBn, respectively. Hammou and Boubaker
The proposed article presents deep learning-based PLDD. The major contributions of this article are summarized as follows:

- PLDD uses DCNN to improve the feature distinctiveness of the plant leaf image features.
- Performance evaluation of proposed PLDD using various performance metrics for the tomato plant.

The remaining article is structured as follows: Section 2 provides a detailed description of the proposed DCNN-based PLDD. Section 3 elaborates on the experimental results and findings from the results. Further, section 4depicts the conclusion and future scope of the work.

2. Related Work

The tremendous global population growth leads to a huge demand increase for food sources and industrial raw materials. The agriculture sector is the prominent source of food and industrial raw material. The economic and social growth of developing countries like India, China, Indonesia, etc., hugely depends upon the growth of the agriculture sector [1-2]. Also, the agriculture sector is the prime source of employment. However, plant disease caused due to adverse climate conditions, less or excess water, pest, viruses, and insects decreases the quality of food and agricultural products [3-5]. Manual disease detection is tedious and inefficient because of various factors such as being prone to error, less accurate due to inadequate knowledge of expert/farmer, less understanding due to vision problems, etc. The leaves of the plants show the disease symptoms reflected in leaf color variation, texture variation, spots on the leaf surface, and damage to the leaf.

Various automatic computer vision-based plant leaf disease detection techniques use ML and DL [6-10].

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The proposed article presents deep learning-based plant leaf disease detection. The major contributions of this article are summarized as follows:

Plant leaf disease detection using DCCN to improve the feature distinctiveness of the plant leaf image features
Performance evaluation of proposed plant leaf disease detection using various performance metrics for tomato plant

The remaining article is structured as follows: Section 2 provides a detailed description of proposed DCNN-based plant leaf disease detection. Section 3 elaborates on the experimental results and findings from the results. Further, section 4depicts the conclusion and future scope of the work.

3. Proposed Methodology

Fig. 1 illustrates the architecture of the proposed deep learning-based PLDD. The proposed DCNN architecture consists of three layers of CNN where each layer consists of a convolution layer (Conv), Rectified Linear Unit Layer (ReLU), and Maximum Pooling Layer(MaxPool). The proposed architecture includes three Conv layers, three ReLU layers, three max MaxPool, one fully connected layer, Softmax classification layer.

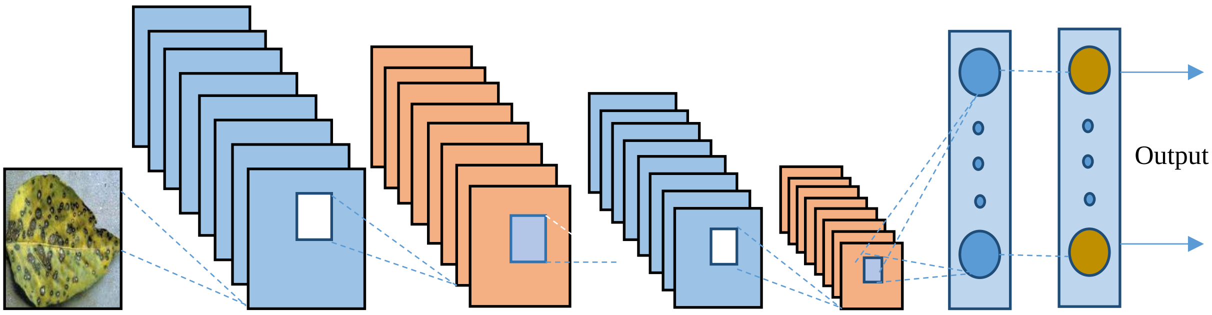


Fig. 1 DCNN architecture of proposed PLDD

The first CNN layer accepts the input color image having dimensions of 200×200×3. The first CNN layer includes the sub-layer such as

$$\{Conv1(NumFilter - 16, Stride - 1) \rightarrow ReLU1(Stride - 1) \rightarrow MaxPool1(Stride - 20)\}$$

The second CNN layer consists of
$\{Conv2(NumFilter - 64, Stride - 1) \rightarrow ReLU2(Stride - 1) \rightarrow MaxPool2(Stride - 20)\}$

and the third CNN layer include
$\{Conv3(NumFilter - 196, Stride - 1) \rightarrow ReLU3(Stride - 1) \rightarrow MaxPool3(Stride - 20)\}$

3.1. Convolution Layer

The convolutional layer presents the deep features of the tomato leaf image. It helps to grab the variations in color, texture, and shape of the leaf image at different CNN layers. Each convolution map provides the distinct characteristics of the leaf images that can distinguish the normal and diseased parts of the leaf. The convolution operation is given by Equations 1 and 2.

$$c(x, y) = im * f \tag{1}$$

$$C(x, y) = \sum_{i=1}^{row} \sum_{j=1}^{col} im(x - i, y - j).f(i, j) \tag{2}$$

Where C is for Conv layer output
im represents the original image
f describes convolution filter kernel
The dimensions of convolution layer output considering striding and padding can be projected using equation 3.

$$D_{out} = \left[\frac{D_{in} - 2P - w}{s} + 1\right] \tag{3}$$

Where w is filter dimensions
p is padding size in pixel
s denotes for striding value in pixel
D_{in} and D_{out} represents original and output image dimensions
The multi-dimensional dimensions of the convolution layer output are provided using equation 4.

$$[row, col, k] * [w, w, N_f] = \left\{\frac{row + 2p - w}{s} + 1, \frac{col + 2p - w}{s} + 1, N_f\right\} \quad (4)$$

Where k stands for no of image channels
w represents filter size
row and col is row and column size of an image
N_f is the number of convolution filters
S stands for striding value
The weights of the convolution filters are initialized randomly before training and updated to optimized value using learning algorithms such as Adam optimizer, stochastic gradient descent (SGD), mini-batch gradient descent (MBGD), algorithms, etc.

3.2. ReLU Layer

The ReLU layer acts as the activation function that improves the non-linearity of the convolutional feature map. It helps to boost the training performance of the network. The ReLU operation is given by equation 5.

$$ReLU(x, y) = \max(C(x, y), 0) \quad (5)$$

3.3. Maximum Pooling Layer (MaxPool)

The MaxPool layer is used to choose the salient features and minimize the dimensions of the deep feature map. Every MaxPool layer halves the original dimensions of the feature map. It helps to minimize the over-fitting problem that arises in deep learning. The MaxPool operation is given by equation 6.

$$MP(x, y) = \max_{\substack{\text{i=1: row−wm,} \\ \text{j=1: col−wm}}} \{ReLU(i + wm - 1, j + wm - 1)\} \quad (6)$$

3.4. Fully Connected Layer

The next layer flattens the multi-dimensional output of the MaxPool3 layer to a one-dimensional vector. The fully connected layer combines all neurons to provide the cumulative representation of all deep feature maps.

3.5. Classification Layer

The Softmax classifier predicts the class label based on the maximum prediction probability of class computed using the Softmax function as given in Equations 7-9.

$$z_i = \sum_j h_j w_{ji} \quad (7)$$

$$p_i = \frac{\exp(z_i)}{\sum_{j=1}^{n} \exp(z_j)} \quad (8)$$

$$\hat{y} = arg \underset{i}{max}\, p_i \quad (9)$$

Where,
z_i stands for the output of the last dense layer
h_j represents the inputs of hidden layers of the last dense layer
w_{ji} are weights of the last dense layer
p_i depicts the probability of the output class
$\hat{y}$ represents output class
The learning of the proposed lightweight DCNN is accomplished using Mini-batch Gradient Descent Algorithm (MBGD) with a batch size of 64 samples and a learning rate of 0.001.

4. Experimental Results and Discussions

The proposed plant leaf disease detection performance is evaluated on the tomato plant of the PlantVillage dataset. Table 1 summarizes the types of diseases and total samples for the experimentation. Fig. 2 shows some of the sample images from the PlantVillage dataset.

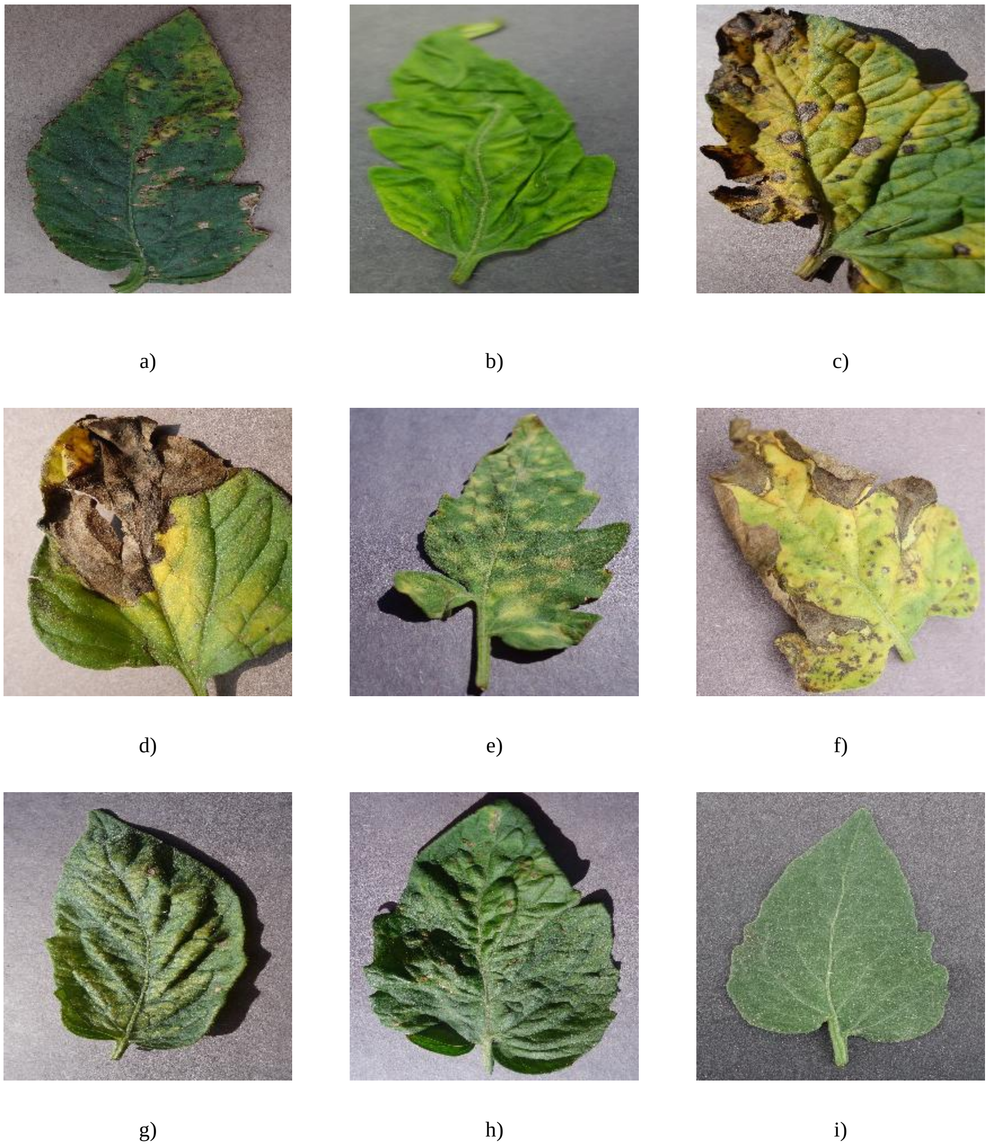


Fig. 2 Samples of tomato plant a) Bacterial spot b) Curl spot c) Early Blight d) Late blight e) Leaf mold f) Septoria leaf spot g) spider mite h) target spot i) Healthy

Table 1. Summary of PlantVillage database (Tomato plant)

Sr. No.	**Type of Defect**	**Total Samples**	**Training Samples (70%)**	**Testing Samples (30%)**
1	Bacterial Spot	2127	1489	638
2	Curl Virus	3209	2246	963
3	Early Blight	1000	700	300
4	Healthy	1591	1114	477
5	Late Blight	1909	1336	573
6	Leaf Mold	952	666	286
7	Septoria Leaf Spot	1771	1240	531
8	Spider Mite	1676	1173	503
9	Target Spot	1404	983	421

Table 2 provides the information about different layers of the proposed DCNN corresponding to feature dimensions, several filters, striding value, activation functions, etc. The results of the proposed DCNN are evaluated based on the Mini-batch Gradient Descent algorithm (MBGD), Stochastic Gradient Descent Momentum (SGDM), Adaptive Moment Estimation (Adam), and Root Mean Square Propagation (RMSP) algorithm.

Table 2. Parameter specifications of proposed DCNN

Layer	Sublayer	Input Dimensions	NumFilter	Filter Size	Stride	Feature Map
Input Layer	256×256×3	-	-	-	-	256×256×3
CNN-I	Conv1	256×256×3	16	3×3	1	256×256×16
	ReLU1	256×256×16	-	-	1	256×256×16
	MaxPool1	256×256×16	-	-	2	128×128×16
CNN-II	Conv2	128×128×16	64	3×3	1	128×128×64
	ReLU2	128×128×64	-	-	1	128×128×64
	MaxPool2	128×128×64	-	-	2	64×64×64
CNN-III	Conv3	64×64×64	195	3×3	1	64×64×196
	ReLU3	64×64×196	-	-	1	64×64×196
	MaxPool3	64×64×196	-	-	2	32×32×196
Fully Connected Layer	FC layer	32×32×196	-	-	-	221184×1
Softmax classifier	-	200704×1	-	-	-	9×1

Table 3. Hyper-parameters of DCNN

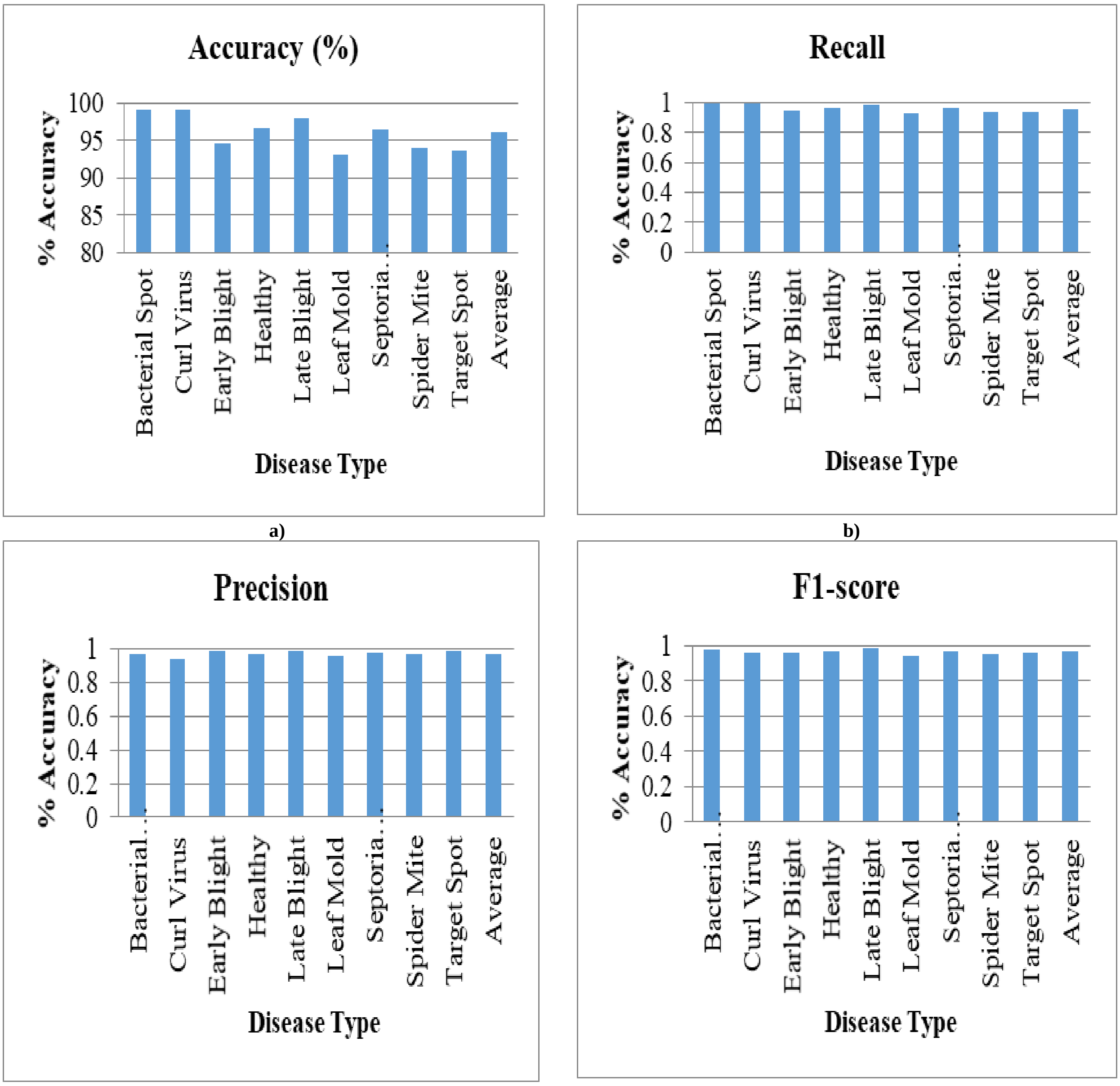
Parameter	**Specifications**
Learning Algorithm	Mini-batch Gradient Descent algorithm
Learning Rate	0.001
Epochs	20
Batch Size	64
Dropout	0.5

The hyper-parameters for the DCNN learning are described in Table 3. The effectiveness of the proposed algorithm is estimated using accuracy, recall, precision, and F1-score for the 9 types of tomato leaf disease such as bacterial spot, curl virus, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, and target spot. Table 4 provides the performance analysis of the proposed scheme for tomato leaf disease detection.

Table 4. Performance of proposed system (9 class disease detection)

Leaf Disease	Accuracy (%)	Recall	Precision	F1-score
Bacterial Spot	99.06	0.9906	0.9693	0.9798
Curl Virus	99.07	0.9907	0.9399	0.9646
Early Blight	94.67	0.9467	0.9827	0.9643
Healthy	96.65	0.9665	0.9705	0.9685
Late Blight	98.08	0.9808	0.9842	0.9825
Leaf Mold	93.01	0.9301	0.9603	0.9449
Septoria Leaf Spot	96.42	0.9642	0.9771	0.9706
Spider Mite	94.04	0.9404	0.9693	0.9546
Target Spot	93.59	0.9359	0.9825	0.9586
Average	**96.06**	**0.96**	**0.97**	**0.97**

The proposed DCNN, along with the MBGD learning algorithm, provides the highest accuracy of 99.07% for the curl virus, followed by 99.06% accuracy for bacterial spot. At the same time, it provides the lowest accuracy of 93.01% and 93.59 % for leaf mold and target spot disease. It provides an average accuracy of 96.06% for 9 types of classes.



a) b) c) d)

Fig. 3 Performance of proposed method for 9 class disease detection a) Accuracy b) Recall c) Precision d) F1-score

The system's performance is also evaluated for the two-class plant leaf disease detection consisting of normal and diseased samples. The proposed system provides 98.83% accuracy for the two-class classification. The various performance metrics for the two-class disease classification are shown in Table 5.

Table 5. Performance of proposed system (2 class classification)

Leaf Disease	Acc	Recall	Precision	F1-score
Healthy	98.59	0.99	0.97	0.98
Disease	99.07	0.99	0.94	0.96
Average	98.83	0.99	0.95	0.97

The outcomes of the DCNN-MBGD are compared with other learning strategies such as DCNN-SGDM, DCNN-Adam, and DCNN-RMSP. The DCNN-MBGD provides 98.83% and 96.06% accuracy for the two classes and nine class classifications. The DCNN-MBGD (98.83%) shows superior performance compared with DCNN-SGDM (97.30%), DCNN-Adam (96.50%), and DCNN-RMSP (95.80%) for 2-class PLDD. The DCNN-MBGD (96.06%) shows superior performance compared with DCNN-SGDM (95.80%), DCNN-Adam (95.20%), and DCNN-RMSP (93.20%) for 9-class PLDD. The DCNN-MBGD gives a precision of 0.97 and 0.95 for the 9-class and 2-class PLDD.

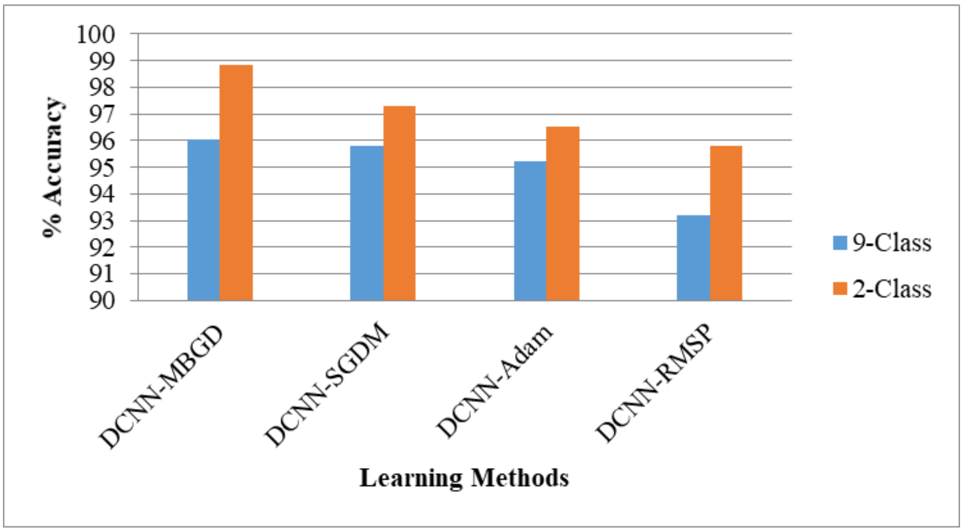


Fig. 4 Accuracy of different learning methods

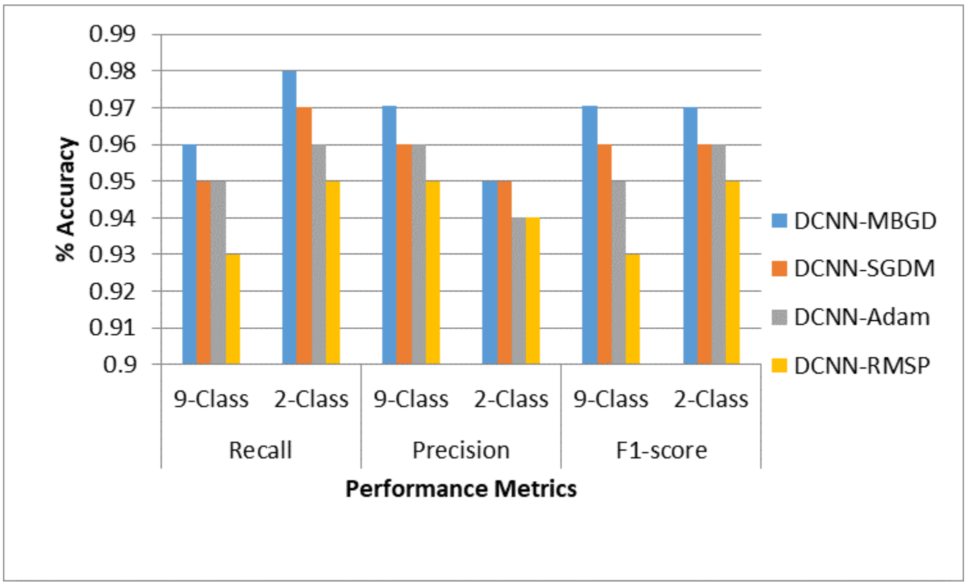


Fig. 5 Recall, precision, and F1-score for 9-class and 2-class PLDD for various learning methods

The performance of the proposed system is compared with traditional techniques used for the PLDD for the tomato plant. It shows noteworthy improvement over the traditional approaches. It provides less number of trainable parameters that further help to minimize the complexity of training and testing of the system. The comparative analysis of the proposed DCNN-MBGD is described in Table 6. The analysis shows that the proposed lightweight architecture of DCNN provides better results for the 2-class (98.83%) and 9-class (96.06%) PLDD. It shows noteworthy improvement in the total trainable parameters that help minimize the proposed architecture's learning and recognition time.

Table 6. performance comparison with Traditional approaches (PlantVillage-Tomato plant)

Author and Year	Number of Classes	Method	Accuracy	Trainable Parameters
Agrawal et al. (2020) [15]	10 classes	ToLeD	91.20%	208802
Karthik R. (2020) [16]	3 classes	Attention-based Residual CNN	98.00%	600000
Fuentes et al. (2022) [13]	9 classes	Faster- RCNN	83.00%	25000000
Proposed method	9 classes	DCNN	96.06%	200704
	2 Class	DCNN	98.83%	

5. Conclusion and Future Scope

Thus, this article provides tomato PLDD based on DCNN. The proposed deep learning model provides distinctive features and higher disease detection accuracy. The proposed algorithm needs no pre-processing of images, and raw real-time images can be fed to the algorithm for disease detection. It provides overall accuracy of 96.06%, recall of 0.96, precision of 0.97, and an F1-score of 0.97 for 9-class detection of tomato disease. It results in 98.83% accuracy for the two-class classification. The performance of the proposed scheme is compared with the traditional state of arts utilized for tomato leaf disease detection, and it is observed that the proposed scheme outperforms the existing state of arts. In the future, the performance of the proposed scheme can be evaluated for real-time disease detection, nutrients prediction, and pesticide prediction.

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