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Detection of Plant Leaf Disease Using a Lightweight Parallel Deep Convolutional Neural Network

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***Abstract*—** Plant diseases and poisonous insects are major threats to agriculture. As a result, detecting and diagnosing these illnesses as soon as feasible is critical. The continuous advancement of significant deep learning techniques has greatly benefited the identification of plant leaf diseases, giving a powerful tool with exceptionally precise findings. The accuracy of deep learning approaches, on the other hand, is reliant on the quality and quantity of labelled data utilized for training. This paper proposes a lightweight parallel deep convolutional neural network (LPDCNN) for plant leaf disease detection (PLDD). Furthermore, a generative adversarial neural network (GAN) is proposed for synthetic data creation in order to address the data scarcity problem caused by unequal dataset size. The suggested model's effectiveness is evaluated using several performance metrics such as accuracy, recall, precision and F1-score and compared to established state-of-the-art methods used for tomato PLDD. The obtained experimental findings - for 2-class, 6-class, and 10-class disease detection of tomato plant samples obtained from the Plant Village dataset – show that the proposed system provides better accuracy (99.14%, 99.05%, 98.11% accuracy for the 2-class, 6-class and 10-class, respectively) for tomato leaf disease detection compared with traditional existing approaches.

***Keywords*—** Deep learning; Convolutional neural network; Plant leaf disease detection; Data augmentation.

1. INTRODUCTION

Agricultural land is more than just a food source in today's world. Plants and fruits are chief sources of energy to both humans and animals. Plant leaves serve an important part in photosynthesis, which is essential for plant growth. Humans benefit from plant leaves because of their medicinal properties. Agriculture provides food, shelter, medicine, and work to more than half of the people in Asian and African countries. Diseases devastate a wide range of agricultural crops, reducing both the amount and quality of production. Plant diseases are classified as parasitic or non-parasitic [1, 2]. Pathogens such as bacteria, viruses, fugus, and cromista can cause parasitic infections, as can pests such as milet, animals, slugs, and rats, and weeds such as monocots and dicots. Non-parasitic plant diseases, on the other hand, might emerge because of an excess or a scarcity of water, temperature, irradiation, minerals, and nutrients. The Indian financial system is profoundly dependent on agricultural productivity. Therefore, Plant Leaf Disease Detection (PLDD) plays chief role in agriculture. It is beneficial to use automatic disease detection technology for early PLDD [3, 4].

The conventional method for detecting plant diseases is merely expert macroscopic inspection through which detection and recognition of plant diseases is carried out. This needs large team of professionals and incessant observations of the system, which is very

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costly for large companies. At the same time, some of the farmers in some countries cannot even be a representative that the appropriate facilities and can contact experts. This is because it costs high and time for advice professionals. In such a state, proposed techniques have been proven advantageous for monitoring large-scale cultural areas. Automatic detection of illness is easier and cheaper by looking at only the symptoms of vegetables leaves. This also assists machine visions for providing image processing based automatic inspection, process control, and robotic guidance [5, 6].

The tomato plant is nutritious and often consumed worldwide. About 160 million tons of tomatoes are consumed annually worldwide [7]. In addition to being rich in nutrients, tomatoes also have medicinal characteristics that can be used to treat hypertension, gingivitis, and hepatitis [8]. It is mostly grown by small farmers and has a significant influence on the agriculture industry. The tomato crop is particularly vulnerable to diseases and pests, which can reduce production by 30 to 50 % [9].

The manual leaf disease diagnosis method requires specialized expertise and is laborious and time-consuming. Due to stress, exhaustion, and a lack of illness interpretation, manual leaf disease detection is often less accurate and ineffective. Therefore, deep learning and autonomous machine learning techniques based on image processing are often used to identify leaf disease [10-12].

Deep neural networks are improvements on the neural network that have lately been effectively used for numerous applications based on computer vision. The layers of nodes used to build deep neural networks are stacked one on top of the other. By adjusting the deep learning layer settings, the performance of the deep learning algorithms may be increased. The size of the database affects the effectiveness of deep learning models [13, 14]. Traditional colour, texture, and form attributes have poor feature representation, which causes illnesses to be misclassified due to a lack of differentiating traits. Previous approaches for defect identification are less universally applicable for illness detection of any sort. Due to their greater hyper parameters, much deep learning architecture provide less flexibility when using real-time data on isolated systems with constrained computing resources. The class imbalance issue is brought about by unequal training samples, which gives the illness class with more training samples greater accuracy than the disease class with fewer training samples [15].

This research paper presents PLDD based on a lightweight parallel convolutional neural network (LPDCNN) to provide the better connectivity of the plant leaf images. The effectiveness of the proposed PLDD scheme is validated for the Tomato plant from the public Plant Village dataset. The major offerings of the research paper are summarized as follow:

- Implementation of tomato PLDD based on LPDCNN for better discriminative feature representation of tomato leaf for leaf disease classification.
- Minimization of computational complexity of deep learning architecture.

The proposed algorithm's performance is evaluated for the synthetic data generated by Generative Adversarial Neural Network (GAN) to diminish the data scarcity problem occurred due to uneven dataset size. The performance of proposed scheme is evaluated for 2-class, 6-class, and 10-class leaf disease detection based on accuracy, precision, recall and F1-score.

The rest of the article is prepared as follows: section 2 provides the associated literature about Plant Leaf Disease Detection. Section 3 gives brief information regarding material and methods required for the implementation of the proposed LPDCNN based PLDD system. Section 4 focuses on the investigational consequences and discussions. Lastly, section 5 elaborates the conclusion and opens the area for the future improvement.

2. RELATED WORK

In agriculture field, disease detection is very important. In recent years, varieties of techniques have been presented for the tomato Plant Leaf Disease Detection (PLDD) using deep learning based techniques. The deep learning based PLDD has attracted the wide attention of researcher's because of its high feature discrimination, more generalization, and larger dataset handling capacity.

Adhikari et al. [16] used YOLO framework for classification of tomato leaf disease detection for three classes that resulted an accuracy of 76.00 %. Karthik et al. [17] presented two CNN architectures based on residual learning and attention mechanism [17]. It is noted that CNN with attention mechanism provides better results (98% accuracy) than residual learning. Durmus et al. [18] investigated SqueezeNet and Alexnet for classification of 10-class tomato disease detection. The SqueezeNet and AlexNet provide an accuracy of 93% and 95.65%, respectively. Elhassouny and Smarandache [19] created mobile application based on Mobile Net for tomato leaf disease detection (9-classes). The mobile application is trained using 7176 images of tomato plant from Plant Village dataset, which has given 90.30% accuracy. Widiyanto et al. [20] utilized a CNN model for tomato PLDD such as Septoria leaf spot, Yellowleaf curl virus, Late blight, mosaic virus and healthy leaves. It has given 96.60% accuracy for model trained on 1000 samples per class. Agrawal et al. [21] presented CNN based deep learning framework (ToLeD) for tomato plant leaf disease detection. They achieved 91.20% accuracy for 10 class classifications, which have shown superiority over traditional MobileNet (63.75%), VGGNet (77.20%), and Inception V3 (63.40%). The lightweight sequential architecture that includes three convolutional and three maximum pooling layers helps to minimize the total trainable parameters and hence the storage space. It has shown variable accuracy for different diseases because of class imbalance problems. Zhang et al. [22] investigated various pre-trained networks such as AlexNet, ResNet, GoogleNet for the tomato plant leaf disease detection. The ResNet along with SGD optimization provided better results compared with AlexNet and GoogleNet. It is observed that proper hyper-parameter tunning helps to improve classification accuracy. Abbas et al. [23] explored Conditional GAN (C-GAN) for the generation of synthetic images to minimize the data scarcity problem and overfitting problem. Additionally, the 5-class, 7-class, and 10-class disease classifications are supported by DenseNet121-based plant leaf disease detection, with respective percentages of 99.51%, 98.65%, and 97.11%. Fuentes et al. [24] employed quicker R-CNN for detecting leaf disease and localization, which has given 85.00% accuracy for the 9-class classification. It uses R-CNN with featured acquired using ResNet50 and VGG-16.

CNN-based deep learning architectures are widely used in a variety of applications utilizing computer vision. In recent years, a number of deep and transfer learning-based PLDD systems have been introduced. Mohanty et al. [25] examined GoogleNet and AlexNet for illness diagnosis across 28 classes, achieving 99.34% and 99.27% accuracy, respectively. Sladojevic et al. [26] investigated anoptimised CNN framework for 13 PLDD distinct plants, yielding 96.30% accuracy. Ramcharan et al. [27] presented transfer learning for identifying illness and damage to cassava plants' paste using GoogleNet (InceptionV3). Prajwala at al. [28] proposed Deep Convolutional Neural Network (DCNN) for the tomato PLDD that has given 94.85% accuracy for the 10-class disease detection. It used the low-resolution images of 60×60 pixels for lighter DCNN architecture. However, the low-resolution images and less deeper architecture may limit the performance of method for the larger real time and high-resolution images. Nazki et al. [29] explored AR-GAN network for the data augmentation and CNN framework for tomato PLDD. It has shown 86.10% accuracy for the 9 classes for Cityscapes dataset. Further, they used CycleGAN [30] with U-net for data augmentation to minimize the data scarcity problem. The complexity of CycleGAN with UNet is higher which may limit the implementation of the system on the standalone system.

Various deep learning frameworks have shown noteworthy improvement in PLDD performance comparatively speaking to conventional machine learning-based algorithms. However, the outcomes of the PLDD based on deep learning frameworks is still challenging because of various factors such as network complexity, larger number of trainable parameters, higher training and recognition time, over-fitting for low disease classes, etc. [31-33]. The generalization capability for PLDD is difficult to achieve which can be used for the all types of PLDD due to differences in the leaf structure, pigmentation level, leaf size, variety in diseases, illumination changes, scale variance and rotation variance of the images. This research uses LPDCNN, which consists of multiple parallel layers of the DCNN that helps to minimize the hyper-parameter tuning problem and improve the feature distinctiveness. This approach provides lightweight solution for the deep learning based PLDD with lower trainable parameters and improves the implementation flexibility on the standalone and portable devices. In this paper, K-means cluster technique is used to get threshold values that are used in classification using Sobel edge detector [34].

3. MATERIALS AND METHODS

3.1. Materials

In this study, Tomato plant samples from the dataset for Plant Village were used. The dataset consists of 10 classes such as one normal and 9 disease classes such as early blight, bacterial spot, late bright mold, leaf mold, target spot, mosaic virus, septoria leaf spot, spider mite, and yellow leaf curl virus. The disease classes are generally grouped into five types such as mold, bacteria, viruses, fungi, and mites diseases [35]. The samples images of the tomato plant are given in Fig. 1.

Table 1 provides the detailed information about disease type, and total samples in dataset. The curl virus disease has maximum samples 3209 whereas mosaic virus includes 373 samples only. Out of the total dataset, samples are chosen for training and testing in proportions of 70% and 30%, respectively.

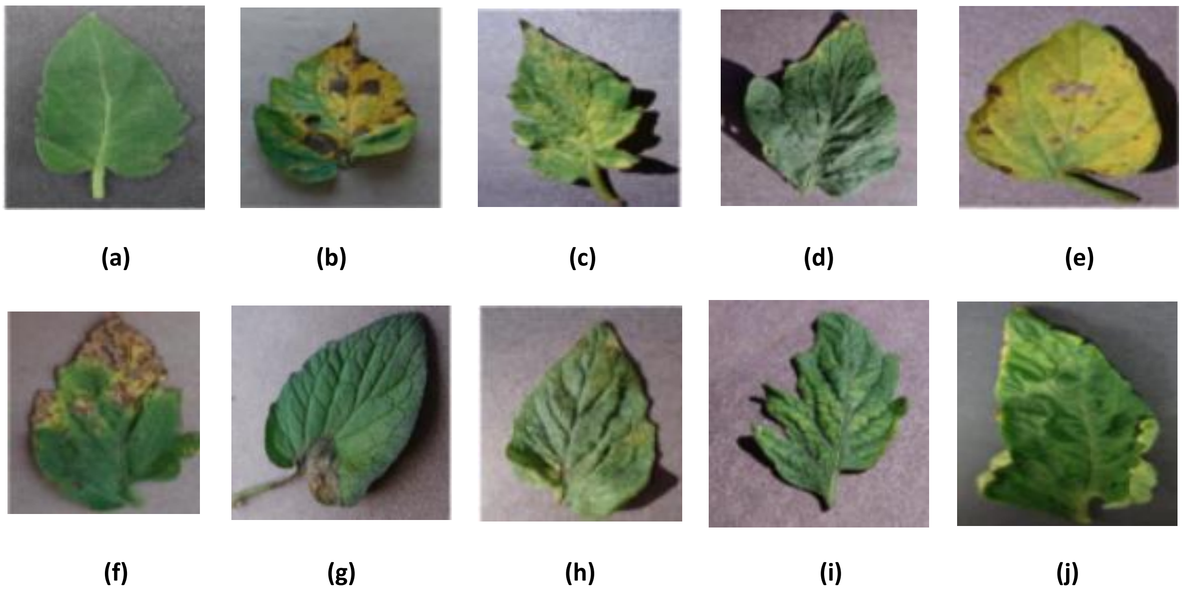

Fig. 1. Samples of the tomato plants from Plant Village dataset: a) healthy; b) early blight; c) leaf mold; d) target spot; e) septoria leaf spot; f) bacterial spot; g) late bright mold; h) spider mite; i) mosaic virus; j) curl virus.

Table 1. Database information (Tomato Plant-Plant Village dataset).

Disease Group	Type of Defect	Original Dataset			Augmented Dataset		
		Total Samples	Study Samples (70%)	Examining Samples (30%)	Total Samples	Study Samples (70%)	Examining Samples (30%)
Healthy	Healthy	1591	1114	477	3500	2450	1050
Viral	Curl Virus	3209	2246	963	3500	2450	1050
	Mosaic Virus	373	261	112	3500	2450	1050
Fungal	Early Blight	1000	700	300	3500	2450	1050
	Septoria Leaf Spot	1771	1240	531	3500	2450	1050
	Target Spot	1404	983	421	3500	2450	1050
	Leaf Mold	952	666	286	3500	2450	1050
Bacterial	Bacterial Spot	2127	1489	638	3500	2450	1050
Mold	Late Brightg mold	1909	1336	573	3500	2450	1050
Mite	Spider Mite	1676	1173	503	3500	2450	1050
Total		16012	11208	4804	35000	24500	10500

3.2. Data Pre-Processing and Data Augmentation

The images of the Plant Village dataset are having variable dimensions; however, for the simplicity, the images are resized to the 256×256×3. The Conditional-Generative Adversarial Network is used for the data augmentation to minimize the over-fitting problem caused due to data imbalance problem. The C-GAN encompasses the generator model and discriminator model. The aim of generator model is to generate the synthetic samples and the aim of discriminator network is to identify synthetic and real samples. The C-GAN takes the advantages of the known labels for the synthetic image generation during training process. The schematic of the C-GAN is illustrated in Fig. 2.

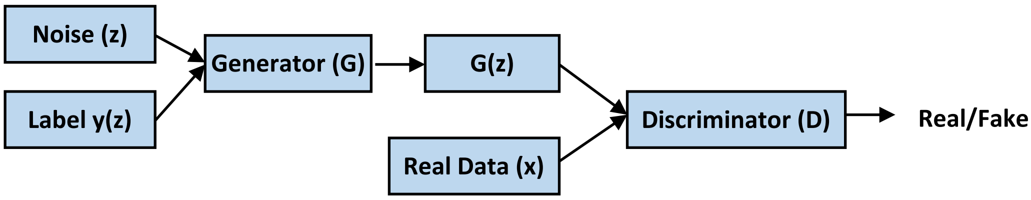

Fig. 2. Structure of C-GAN.

The C-GAN generator encompasses input layer, dense layer, embedding layer, leaky ReLU layer, reshape layer, concatenate layer, four convolution layer where every layer followed by leaky ReLU layer. Model E of the C-GAN discriminator encompasses input layer, layer of embedding, layer of dense, reshape layer, concatenate layer, four-convolution layer followed by leaky ReLU layers, flattening layer and dropout layer. The generator model (G) creates the synthetic images using random noise and latent points whereas discriminator model (D) detects the real and fake samples produced by the G model [36, 37].

The input noise and latent point distribution fed to G is given by $n_z(z)$. The image samples im and class labels y are provided to discriminator model. The D model attempts to boost the probability allocating class labels to original data and synthetic images are given by $logD(im|y)$. The G model assists to reducethe loss of the generator and it is given by $\log(1 - \mathrm{D}(\mathrm{G}(\mathrm{z}|\mathrm{y}))$. The C-minmax GAN's goal function is given in Eq. (1).

$$\min_G \max_D(G, D) = E_{im\sim p_{data}(im)}[logD(im|y)] + E_{z\sim p_z(z)}[\log(1 - \mathrm{D}(\mathrm{G}(\mathrm{z}|\mathrm{y})))] \quad (1)$$

3.3. Network Model

The proposed LPDCNN consists of four parallel DCNN structures where each parallel arm consist of different filter dimensions such as 3×3, 5×5, 7×7, and 9×9 as given in Fig. 3. The used of different filter size helps to acquire the fine and course textural information of the leaf image. Each arm DCNN includes three levels of convolution ($Conv - 2D$), three layers of Rectified Linear Units ($ReLU$) with a maximum of three pooling layers ($MaxPool$). The convolution layer provides the correlation and connectivity between specific local sections of the plant leaf surface. It can characterize distinguishing characteristics of plant leaf texture, edges, surface, and form. The input leaf picture is convolved using several convolutional filters in this layer. The feature maps produced by each filter may reflect various leaf properties. The convolution operation is given by Eq. (2) where im is original leaf image, w is convolution filter, row and col are total rows and columns of image matrix.

$$C(x, y) = \sum_{i=1}^{row} \sum_{j=1}^{col} im(i, j) * w(x - i, y - i) \quad (2)$$

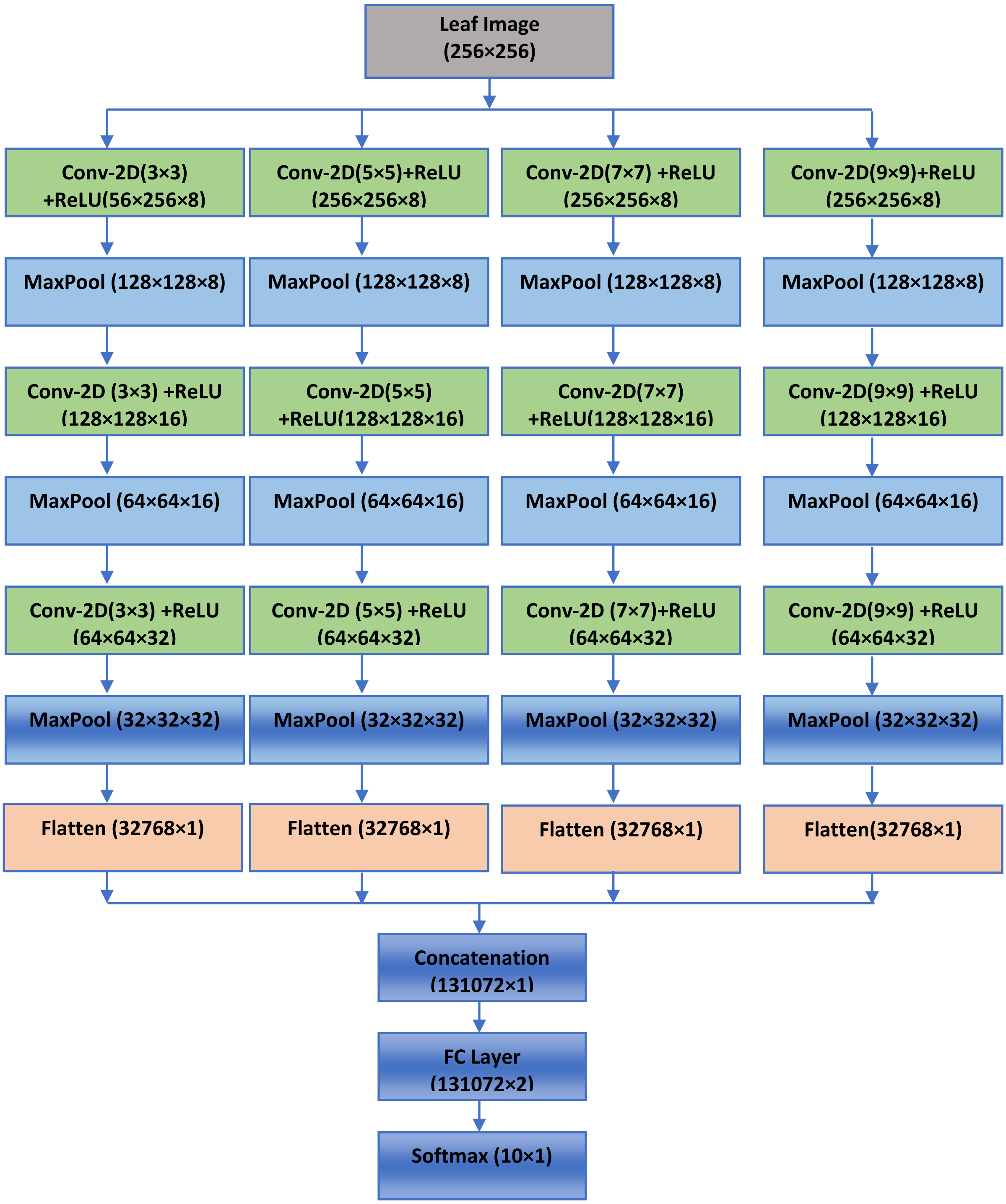

Fig. 3. Network architecture of the proposed system.

In the ReLU layer, all negative values from the output of the convolutional layer are rounded to zero while non-negative values are left alone. The issue of disappearing gradients is mitigated by the ReLU activation function, allowing CNN features to be trained quicker and more efficiently. It introduces non-linearity into the data, making it easy to optimize. Eq. (3) gives the ReLU operation.

$$R(x,y) = \begin{cases} 0 & if\ C(x,y) < 0 \\ C(x,y) & otherwise \end{cases} \tag{3}$$

The maximum pooling layer chooses the largest pooling window to lower the feature maps and capture the key information from the crop leaf [38–41]. Eq. (4) provides the maximum pooling operation for 2×2 window with stride of two pixels considering non-overlapping window.

$$M(i,j) = \max_{\substack{i=1:2:row \\ j=1:2:col}} (R(i:i+1, j:j+1) \quad (4)$$

After third $MaxPool$ layer, the feature maps are flattened to convert multi-dimensional feature map to one dimensional vector to analyze the effect of different filter size on the PLDD. All four arms flattened features are concatenated together which are further given to fully connected layer. In the last layer, the probability based Softmax classifier is used for classification. The LPDCNN model is trained using ADAM optimization algorithm for the learning rate of 0.001, batch size of 64, and 300 epochs.

4. EXPERIMENTAL FINDINGS AND DISCUSSIONS

The proposed system is built on the Nvidia GPU with 512 tensor-core and 16 GB RAM. Figs. 4 to 7 summarize the suggested LPDCNN model's performance for 10-class categorization of tomato PLDD based on accuracy, recall, precision and F1-score, respectively. When the proposed model is trained for original data, it gives higher accuracy for the curl virus (99.58%), healthy (98.74%) and late bright mold (98.60%). However, it provides the lower disease detection accuracy for the mosaic virus (88.39%) and leaf mold (91.96%) diseases because of lower training samples that creates class imbalance problem. When the suggested model for the enhanced dataset is trained (2450 samples per class), it results in higher accuracy for the curl virus (99.58%), late bright mold (99.13%), bacterial spot (98.90%) and healthy samples (98.74%). The data augmentation using C-GAN helps to minimize the class imbalance problem and provides improved accuracy for mosaic virus (96.43%) and leaf mold (96.50%) diseases. The proposed LPDCNN-CGAN shows 2.15% improvement over the disease detection accuracy over the LPDCNN without data augmentation for 10-class disease detection. The F1-score provides the balance in the performance of the 10-class disease detection.

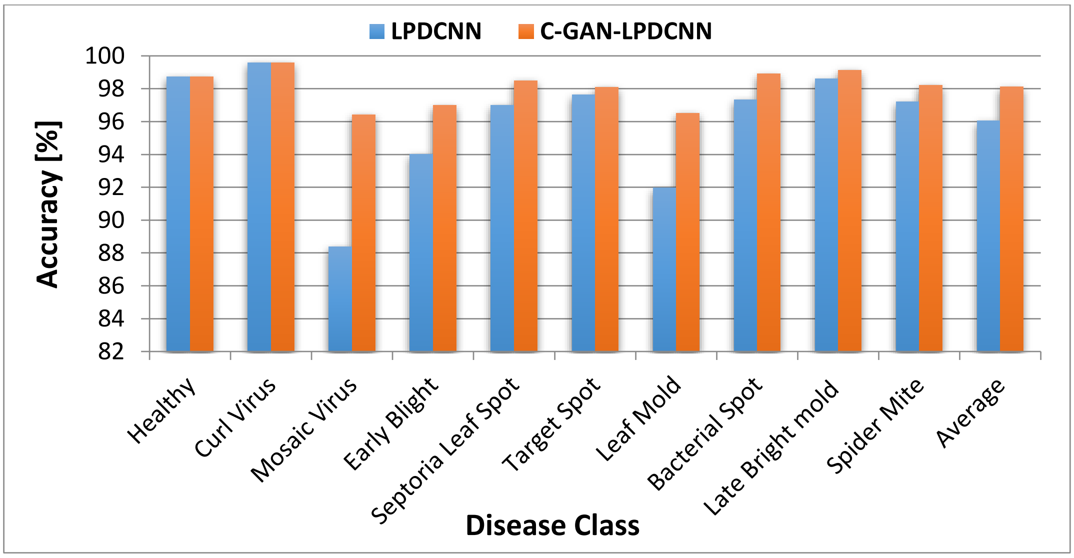

Fig. 4. Accuracy for the proposed LPDCNN with and without data augmentation for 10-class tomato leaf disease.

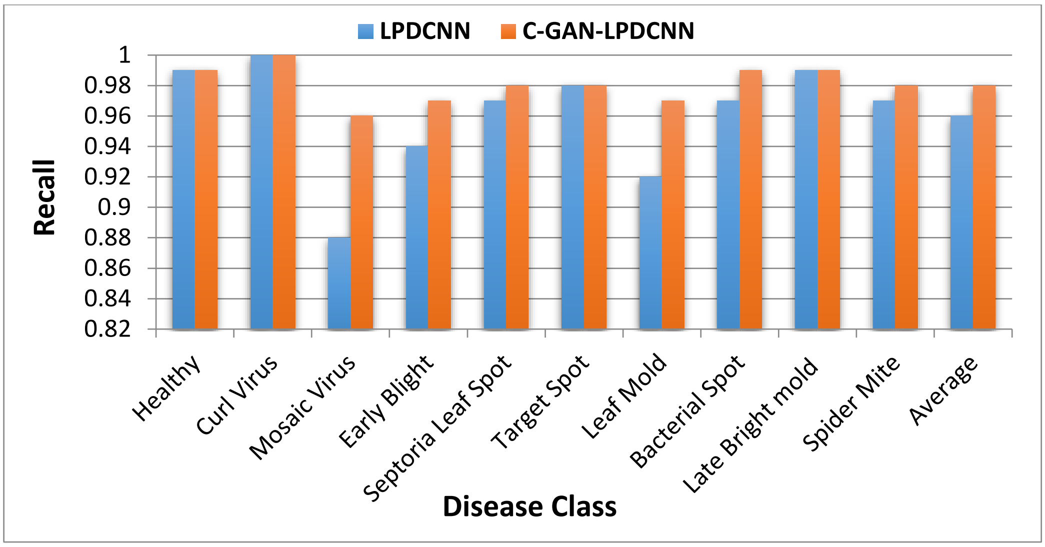

Fig. 5. Recall for the proposed LPDCNN with and without data augmentation for 10-class tomato leaf disease.

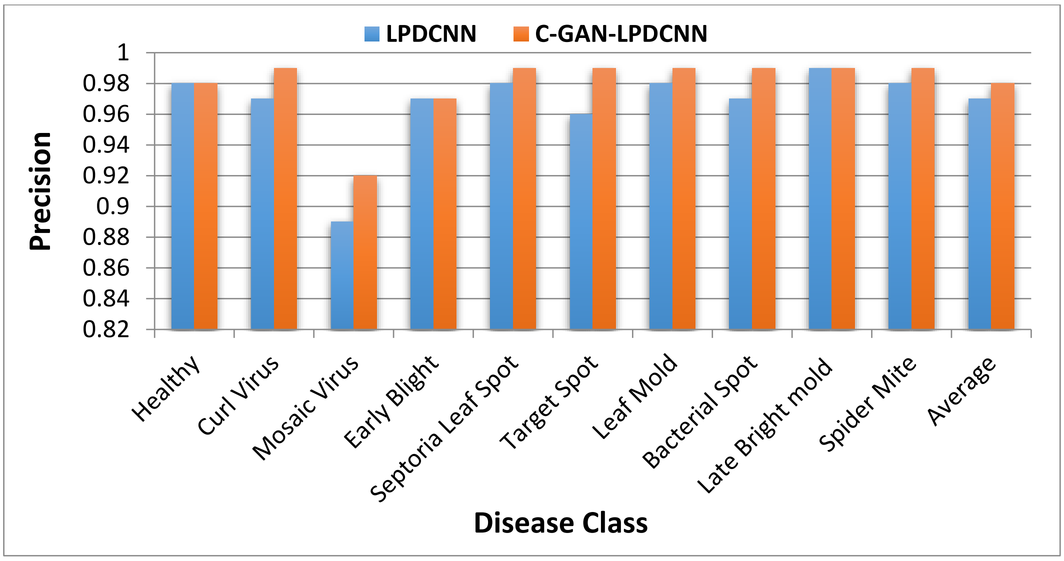

Fig. 6. Precision for the proposed LPDCNN with and without data augmentation for 10-class tomato leaf disease.

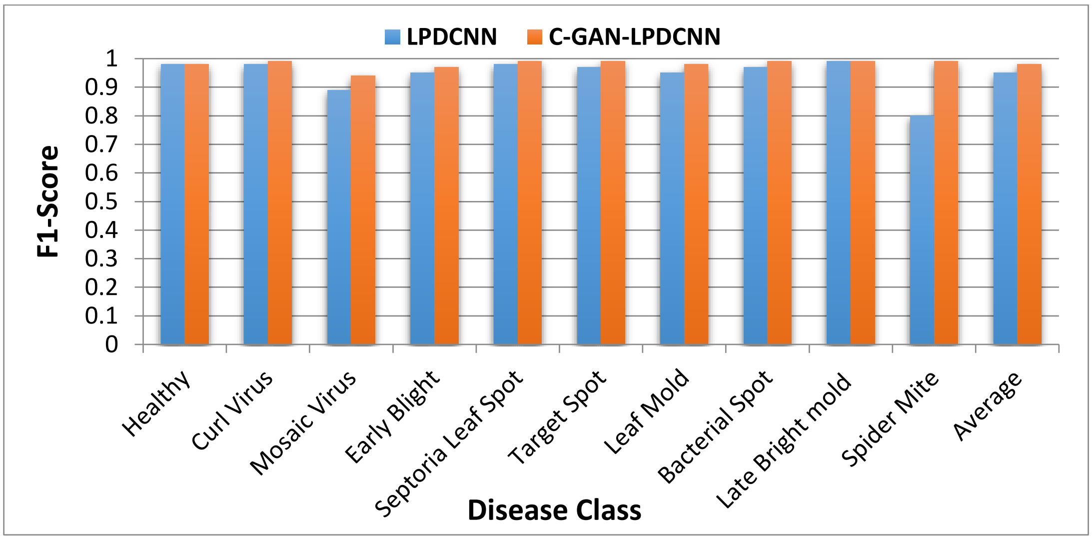

Fig. 7. F1-score for the proposed LPDCNN with and without data augmentation for 10-class tomato leaf disease.

Fig. 8 provides the results of the proposed LPDCNN for the 6-class disease detection that includes healthy, viral, fungal, bacterial, mold and mite classes. The proposed LPDCNN provides 99.05% and 97.96% accuracy when the proposed model is trained for dataset without and with data augmented samples respectively.

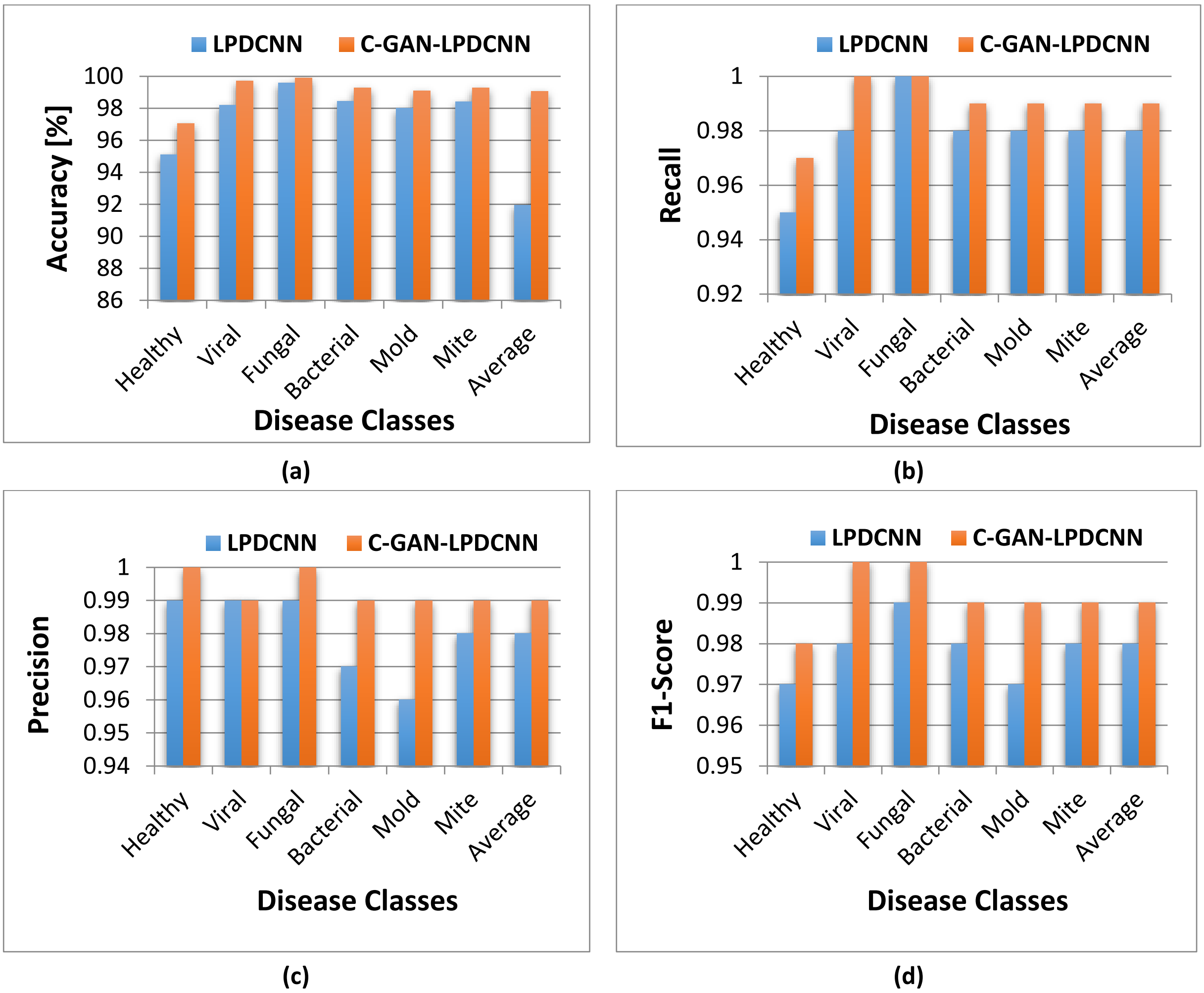

Fig. 8. Performance of the proposed LPDCNN without and with data augmentation for 6-class tomato leaf disease: a) accuracy; b) recall; c) precision; d) F1-score.

The proposed LPDCNN's performance is also verified for two-class illness detection, which covers healthy and sick classes. The suggested method achieves 99.14% LPDCNN-CGAN accuracy and 97.87% LPDCNN accuracy without data augmentation. Fig. 9 shows the various performance measures for detecting leaf disease.

The outcomes of the LPDCNN are evaluated for the one, two and three parallel DCNN layers on the architecture. It is observed that three parallel-layered architecture helps to capture the distinctive features with different filter size in each layer. The average results of LPDCNN for different number of parallel arm are shown in Fig. 10. Increasing more parallel layers leads to increase in total trainable parameters, thus the number of parallel layers are limited to 4 layers.

Table 2 compares the efficacy of the proposed LPDCNN-based PLDD to the traditional state-of-the-art plant leaf disease identification. The LPDCNN provides 99.14% and 97.87% accuracy for 2-class disease detection with and without data augmentation respectively, which is superior compare with ResNet (97.28%) for tomato class [22]. It resulted in 98.11%

and 96.04% accuracy for 10-class disease detection with and without data augmentation. It resulted in 99.05% and 97.96% accuracy for the 6-class PLDD. The proposed LPDCNN provides 7.57% and 1.02% improvement over ToLeD [21] and DenseNet121 [23] respectively for 10-class classification tomato PLDD. The parallel architecture helps to achieve the better connectivity in local and global features of the plant leaf image that improves the discriminative capability of the defected area on leaf surface.

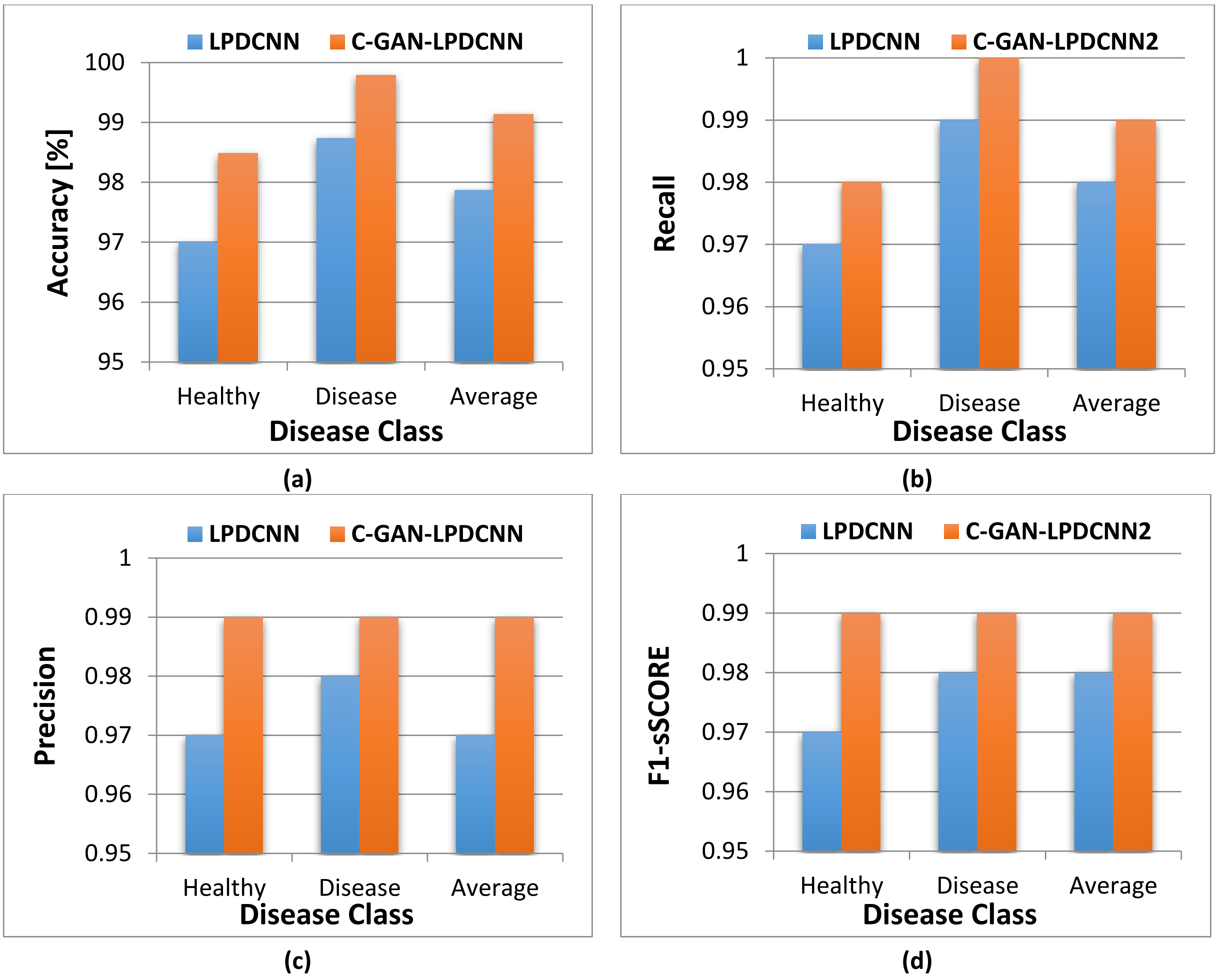

Fig. 9 Performance of the proposed LPDCNN with and without data augmentation for 2-class tomato leaf disease: a) accuracy; b) recall; c) precision; d) F1-score.

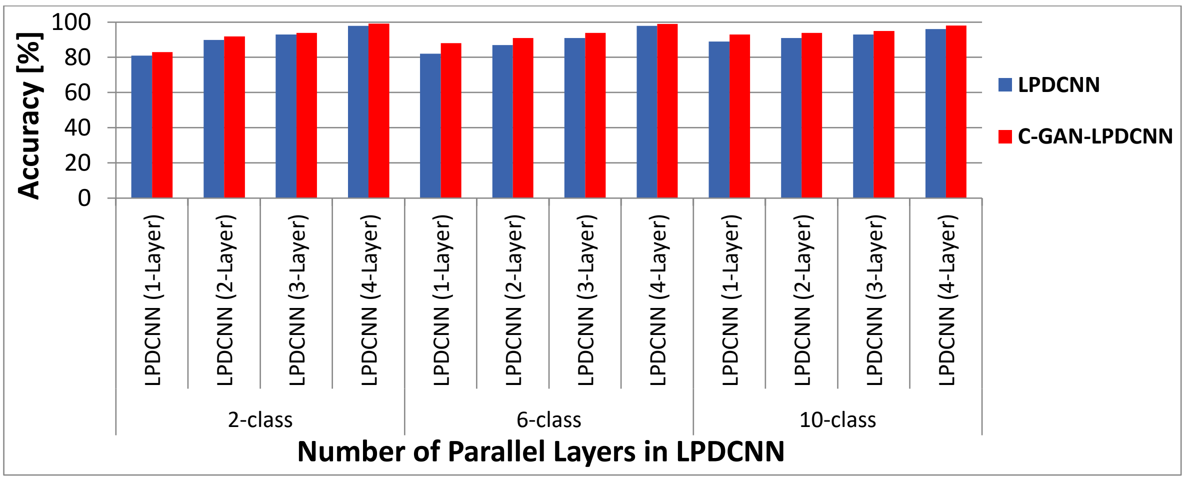

Fig. 10. Accuracy of the proposed model for different parallel arms in LPDCNN (2, 6 and 10s-class classification).

Table 2. Performance of the proposed versus the conventional methods (Tomato Plant Village dataset).

Ref.	Method	Number of Classes	Performance			
			Accuracy	Recall	Precision	F1-score
[21]	ToLeD	10	91.20%	0.92	0.90	0.91
[22]	ResNet with SGD optimization	2	97.28%	-	-	-
[23]	C-GAN + DenseNet121	5	99.51%	0.99	0.99	0.99
		7	98.65%	0.99	0.98	0.98
		10	97.11%	0.97	0.97	0.97
Proposed Method	LPDCNN (Without data augmentation)	2	97.87	0.98	0.97	0.98
		6	97.96	0.98	0.98	0.98
		10	96.04	0.96	0.97	0.95
	C-GAN-LPDCNN-CGAN (With data augmentation)	2	99.14	0.99	0.99	0.99
		6	99.05	0.99	0.99	0.99
		10	98.11	0.98	0.98	0.98

The proposed lightweight LPDCNN provides 122882, 155654, 188426 trainable parameters for two-class, six-class, and ten-class tomato PLDD. It shows significant reduction in trainable parameters compared with ToLeD (208802) [15], ResNet (31.7M), and DenseNet-121 (10.4M) [17] that helps to minimize the computational complexity of the network. It needs lower quantity of trainable parameters to increase the feasibility of the implementation of the proposed system on standalone portable devices in future.

5. CONCLUSIONS AND FUTURE WORK

This paper presented a lightweight parallel DCNN in order to identify tomato plant leaf disease that increases the feature distinctiveness and minimizes problem of filter size selection. Further, cyclic generative adversarial network (CGAN) was effectively implemented for the synthetic image creation that helps to diminish the class imbalance problem occurred due to uneven samples in the training dataset. The proposed LPDCNN helped to improve the feature representation of leaf images and assisted to boost the PLDD accuracy for multiple diseases. The proposed LPDCNN provided 99.14%, 99.05%, 98.11% accuracy for the 2-class, 6-class and 10-class disease detection for tomato PLDD from Plant Village dataset. The proposed LPDCNN-CGAN showed 2.15% improvement over the disease detection accuracy over the LPDCNN without data augmentation for 10-class disease detection. The proposed algorithm provided less trainable parameters (188426) for the 9 class PLDD which is superior over the traditional state-of-arts and helped to increase the possible implementation flexibility on the standalone devices. The proposed model provided better results in comparison to established state-of-the-art methods for detecting tomato plant leaf disease. In future, the proposed network can be made deeper and utilized for multiple plants leaf disease detection. Additionally, the performance of the proposed scheme can be evaluated for the real time PLDD for multiple disease detection for multiple crops. Further, the learning of the LPDCNN can be optimized using optimization algorithm to improve the networks performance.

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