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Parallel deep CNN for tomato leaf disease detection

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ABSTRACT

Agriculture faces significant risks from plant diseases and venomous insects, highlighting the crucial need for swift detection and diagnosis of these disorders. Continuous advancements in deep learning (DL) techniques have significantly facilitated the identification of plant leaf diseases, providing accurate and powerful tools. The accuracy of DL methods heavily depends on the quality and quantity of labeled samples used during training. This article introduces Tomato leaf disease detection using a Parallel Deep Convolutional Neural Network (TPDCNN) for plant leaf disease detection (PLDD). Additionally, it presents the use of a Conditional Generative Adversarial Neural Network (C-GAN) for generating artificial data to address the issue of limited data availability caused by imbalanced dataset sizes. Experimental results are conducted using the PlantVillage dataset (tomato plants), focusing on two-, six-, and ten-class PLDD. The effectiveness of the TPDCNN model is evaluated through various performance measures, including accuracy, recall, precision, and F1-score, and compared against traditional state-of-the-art approaches used for detecting tomato plant leaf diseases. The proposed system outperforms existing methods, achieving superior accuracy rates (99.14% for 2-class, 99.05% for 6-class, 98.11% for 10-class PLDD) for tomato PLDD. The TPDCNN method is well-suited for real-time deployment on standalone devices with limited computational resources due to its simpler structure and fewer trainable parameters.

Contribution/ Originality: Using a conditional GAN and a parallel CNN, this study suggests a unique approach for detecting tomato leaf disease. While the C-GAN creates artificial samples to reduce class imbalance, the parallel CNN enhances feature extraction, providing a lightweight, effective deep-learning architecture suitable for real-time, resource-constrained deployment.

1. INTRODUCTION

In today's world, agricultural land serves a greater purpose than just being a source of food. Plants and fruits are essential energy sources for both humans and animals, with plant leaves playing a crucial role in photosynthesis and overall plant growth. Plant leaves also possess medicinal properties that benefit humans. Agriculture plays a vital role in Asian and African countries, providing food, shelter, medicine, and employment for over half of their populations. However, diseases pose a significant threat to agricultural crops, resulting in reduced quality and quantity of products [1, 2].

Plant diseases can be classified as parasitic or non-parasitic. Parasitic diseases are caused by pathogens such as bacteria, viruses, fungi, and chromista, as well as pests like mites, slugs, animals, and rodents, and weeds such as dicots and monocots. Conversely, non-parasitic plant diseases can occur due to factors like water excess or shortage, temperature fluctuations, irradiation, mineral imbalances, and nutrient deficiencies. The Indian economy heavily relies on agricultural yield, making PLDD a crucial aspect of agriculture. Therefore, adopting automatic disease detection technology for early PLDD is beneficial [3-5].

The conservative method of detecting plant diseases relies on expert macroscopic examination, which is a labor-intensive and costly process, requiring a large group of specialists and continuous observations [6]. In some cases, farmers in certain countries lack access to appropriate facilities and experts, making it challenging to seek advice due to high costs and time constraints. In such situations, the proposed techniques prove advantageous for monitoring large-scale agricultural areas. By focusing solely on the symptoms exhibited by plant leaves, automatic detection of illnesses becomes easier, cheaper, and assists in image processing-based automatic inspection, process monitoring, process control, and remote robotic guidance through machine vision [7, 8].

Tomatoes are a widely consumed and nutritious crop, with an annual global consumption of approximately 160 million tonnes. Apart from their nutritional value, tomatoes possess medicinal properties that can be used to treat gingivitis, hypertension, and hepatitis. Tomatoes are predominantly grown by small farmers and significantly contribute to the agriculture industry. However, tomato crops are susceptible to diseases and pests, which can lead to a decrease in production by 30 to 50 percent. Manual leaf disease diagnosis methods require specialized expertise and are time-consuming and laborious.

They often lack accuracy and effectiveness due to factors such as stress, fatigue, and subjective interpretation of illnesses. To overcome these challenges, deep learning (DL) and machine learning (ML) techniques based on image processing are commonly employed for leaf disease identification [9-11].

Deep neural networks, a significant improvement over traditional neural networks, have proven to be highly effective in various computer vision applications. These networks consist of stacked layers of nodes, and by adjusting their settings, the effectiveness of DL algorithms can be enhanced. However, the effectiveness of DL models is influenced by the size of the database used for training. Traditional color, texture, and shape attributes may not provide sufficient feature representation, leading to the misclassification of diseases due to a lack of distinguishing characteristics [12, 13].

Previous approaches to defect identification may not be universally applicable for detecting various types of illnesses. Additionally, many deep learning architectures with higher hyperparameters may offer less flexibility when operating in real-time scenarios with limited computing resources. Class imbalance issues arise when training samples are unevenly distributed, resulting in higher accuracy for the disease class with larger training data compared to the class with fewer data [14, 15].

This research paper introduces a PLDD system based on a lightweight TPDCNN to improve the connectivity of plant leaf images. The proposed PLDD scheme is validated using the Tomato plant dataset from PlantVillage. The key contributions of this research paper are as follows.

- Implementation of a tomato PLDD system based on TPDCNN for superior discriminative feature representation of tomato leaves, leading to accurate PLDD and reduced computational complexity of the DL framework.
- Evaluation of TPDCNN's performance using artificial data generated by GAN to address the issue of data scarcity resulting from imbalanced datasets.
- Performance assessment of the proposed scheme for 3, 6, and 10-class PLDD, based on metrics such as accuracy, recall, precision, and F1-score.

The remaining article is organized as follows: Section 2 provides a review of the relevant literature on PLDD using ML and DL. Section 3 presents the dataset details and methods required for implementing the proposed TPDCNN-based PLDD scheme. Section 4 emphasizes the experimental results and discussions. Finally, Section 5 concludes the article and suggests avenues for future improvements.

2. RELATED WORK

In the field of agriculture, disease identification plays a crucial role. DL-based techniques have gained significant attention in recent years for tomato PLDD due to their high feature discrimination, generalization capability, and ability to handle large datasets.

Adhikari et al. [16] utilized the YOLO architecture to classify tomato PLDD into three classes, achieving an accuracy of 76.00%. However, the complex architecture and larger trainable parameters (27.6M) make it difficult to deploy on standalone devices. Karthik et al. [17] presented two CNN architectures based on residual learning along with an attention scheme.

Their results indicated that the CNN with the attention scheme outperformed residual learning, achieving an accuracy of 98%. Durmuş et al. [18] investigated the performance of AlexNet and SqueezeNet for classifying 10 different tomato diseases, with SqueezeNet achieving an accuracy of 93% and AlexNet achieving 95.65%. Elhassouny and Smarandache [19] developed a mobile application based on MobileNet for detecting nine classes of tomato leaf diseases. Their model, trained on 7176 tomato plant images from the PlantVillage dataset, achieved 90.30% accuracy. Widiyanto et al. [20] employed a CNN model for PLDD, focusing on diseases such as Septoria leaf spot, curl virus, yellow leaf, late blight, mosaic virus, and healthy leaves, resulting in an accuracy of 96.60% with a dataset of 1000 samples per class.

Agarwal et al. [21] proposed a CNN-based framework (ToLeD) for tomato PLDD, achieving an accuracy of 91.20% for 10-class classification. Their model demonstrated superiority over traditional approaches such as VGGNet (77.20%), MobileNet (63.75%), and Inception V3 (63.40%). The proposed lightweight cascaded architecture, consisting of three convolutional and maximum pooling layers, helped reduce the number of trainable parameters and storage space.

However, the accuracy varied for different diseases due to class imbalance issues. Zhang et al. [22] explored pre-trained networks such as AlexNet, ResNet, and GoogleNet for tomato PLDD. The ResNet model, combined with SGD optimization, yielded better results compared to AlexNet and GoogleNet, highlighting the importance of hyper-parameter tuning.

Abbas et al. [23] explored Conditional GAN (C-GAN) for generating artificial images to address data scarcity and overfitting issues. Their DenseNet121-based PLDD achieved accuracies of 99.51% for 5-class, 98.65% for 7-class, and 97.11% for 10-class PLDD. Fuentes et al. [24] employed Faster R-CNN for leaf disease detection and localization, achieving an accuracy of 85.00% for a 9-class classification using ResNet50 and VGG-16 features.

DL architectures based on CNNs have gained widespread acceptance in various computer vision systems. Several DL and transfer learning (TL)-based PLDD systems have been proposed in recent years. Mohanty et al. [25] proposed AlexNet and GoogleNet for 28-class PLDD, achieving accuracies of 99.34% and 99.27% for GoogleNet and AlexNet, respectively.

Sladojevic et al. [26] investigated a fine-tuned CNN for PLDD across 13 different plants. The method resulted in 96.30% accuracy for 13-class PLDD. Ramcharan et al. [27] proposed TL based on GoogleNet (InceptionV3) for detecting pest damage and diseases in cassava plants. Prajwala et al. [28] introduced a DCNN for tomato PLDD, achieving an accuracy of 94.85% for a 10-class disease detection task. Their approach utilized low-resolution images (60×60 pixels) to create a lighter DCNN architecture.

However, this approach may have limitations when handling larger real-time high-resolution images. Nazki et al. [29] employed an AR-GAN network for data augmentation and a CNN for tomato PLDD, achieving 86.10% accuracy for nine classes using the Cityscapes dataset. They also utilized CycleGAN with U-net for data augmentation to address data scarcity, but noted that the complexity of CycleGAN with U-net might limit implementation on standalone systems. Badiger and Mathew [30] presented a hybrid deep learning framework for tomato plant leaf disease segmentation and multiclass classification. They used a deep batch-normalized ELU AlexNet (DbneAlexNet) model enhanced with Gradient-Golden Search Optimization for U-Net segmentation and Gradient Jaya-Golden

Search Optimization for classification. This unified segmentation and classification approach achieved a high accuracy of 92.4%, with superior TPR, TNR, and low FPR, demonstrating its effectiveness for early and accurate tomato disease detection. In recent years, advanced deep learning frameworks have been deployed for disease detection in tomato plants. Yulita et al. [31] proposed a DenseNet-based deep learning model for tomato plant leaf disease detection implemented in a mobile application. By optimizing hyperparameters and using two hidden layers with a dropout rate of 0.4, they achieved 95.7% accuracy and a 95.4% F1-score under 10-fold cross-validation, highlighting the feasibility of smartphone-based real-time tomato disease monitoring. Tang et al. [32] developed PLPNet, a precise image-based tomato leaf disease detection method.

They introduced a perceptual adaptive convolution module, a location reinforcement attention mechanism, and a proximity feature aggregation network to address issues such as soil background interference and interclass similarity. PLPNet achieved 94.5% mAP50, outperforming common detectors and providing a robust tool for modern tomato cultivation. Ahmed et al. [33] focused on prompt detection of tomato leaf diseases using a hybrid transfer learning approach. By combining transfer learning with conventional machine learning, they developed the XSVC model, which classified nine diseases and healthy leaves with 99.51% accuracy on 60,000 images. They also created an Android app for real-time disease prediction, advancing automated tomato disease diagnosis.

Billah et al. [34] proposed a neural network approach for identifying five major tomato leaf diseases, including bacterial and viral infections. Using color, shape, and texture features extracted from segmented images, their method achieved nearly 99% classification accuracy, emphasizing the need for adaptable algorithms and customized strategies for precision in leaf disease identification. Kaur et al. [35] examined the performance of segmentation models for detecting tomato leaf diseases, assembling a hybrid deep segmentation CNN (DSCNN) model from U-Net and Seg-Net pre-trained networks with instance segmentation. This hybrid approach improved detection of single and multiple leaf diseases and outperformed other modified U-Net and Seg-Net models in accuracy, precision, recall, IoU, and mIoU, demonstrating its efficiency for large-scale segmentation tasks. Wang and Liu [36] introduced TomatoDet, a novel model for detecting four common tomato diseases and healthy leaves in complex backgrounds. They integrated Swin-DDETR's self-attention mechanism, the Meta-ACON activation function, and an improved bidirectional weighted feature pyramid network (IBiFPN) to enhance small-target localization and reduce false positives and negatives. Their model achieved 92.3% mAP and 46.6 FPS, marking a significant improvement over baselines in real-world conditions. Sun et al. [37] proposed an advanced tomato disease recognition system based on the exponential moving average and data-efficient transformer (EMA-DeiT) model, which combines the data-efficient image transformer with exponential moving average and self-distillation strategies. Their system achieved 99.6% accuracy on the PlantVillage dataset and over 97% on multiple external datasets, demonstrating strong generalization and practical value for precision agriculture. DL frameworks have demonstrated significant improvements in PLDD effectiveness compared to traditional ML algorithms. However, challenges still exist due to aspects such as tedious hyperparameter tuning, complexity in architecture, large numbers of trainable parameters, longer training and recognition times, and overfitting issues for diseases with fewer instances [38-40].

3. MATERIAL AND METHODOLOGY

3.1. Dataset

In this work, tomato leaf images were obtained from the PlantVillage dataset. The dataset comprises a total of 10 classes, including one normal class and nine disease classes: early blight, bacterial spot, septoria leaf spot, late blight mold, leaf mold, mosaic virus, target spot, yellow leaf curl virus, and spider mite. These disease classes can be categorized into five categories: bacterial, viral, mold, fungal, and mite diseases [41]. Figure 1 illustrates sample images of the tomato plant, while Table 1 provides comprehensive information about the disease types and the total number of images in the dataset. Among the disease classes, curl virus disease has the highest number of images (3209), while mosaic virus disease includes only 373 images. The augmented dataset consists of 3500 samples per class. For the training and testing of the models, 70% of the total dataset was allocated for training, and the remaining 30% was used for testing purposes.

a) Healthy b) Early Blight c) Leaf mold d) Target spot e) Septoria leaf spot

f) Bacterial spot g) Late blight mold h) Spider mite i) Mosaic virus j) Curl virus

Figure 1. Samples of the tomato plant from the PlantVillage dataset.

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

Disease group	**Healthy**	**Viral**		**Fungal**				**Bacterial**	**Mold**	**Mite**	**Total**
Disease type	**Healthy**	**Curl virus**	**Mosaic virus**	**Early blight**	**Septoria leaf spot**	**Target spot**	**Leaf mold**	**Bacterial spot**	**Late blight mold**	**Spider mite**	
Original Samples	1591	3209	373	1000	1771	1404	952	2127	1909	1676	16012
Augmented Samples	3500	3500	3500	3500	3500	3500	3500	3500	3500	3500	35000

3.2. Data Pre-Processing and Data Augmentation

To ensure simplicity and consistency, the images from the Plant Village dataset were resized to 256×256×3 dimensions. Data augmentation was performed using a C-GAN to address the issue of overfitting resulting from data imbalance, as given in Figure 2. The C-GAN consists of both a generator and a discriminator model. The generator's objective is to generate artificial samples, while the discriminator's role is to distinguish between synthetic and real samples.

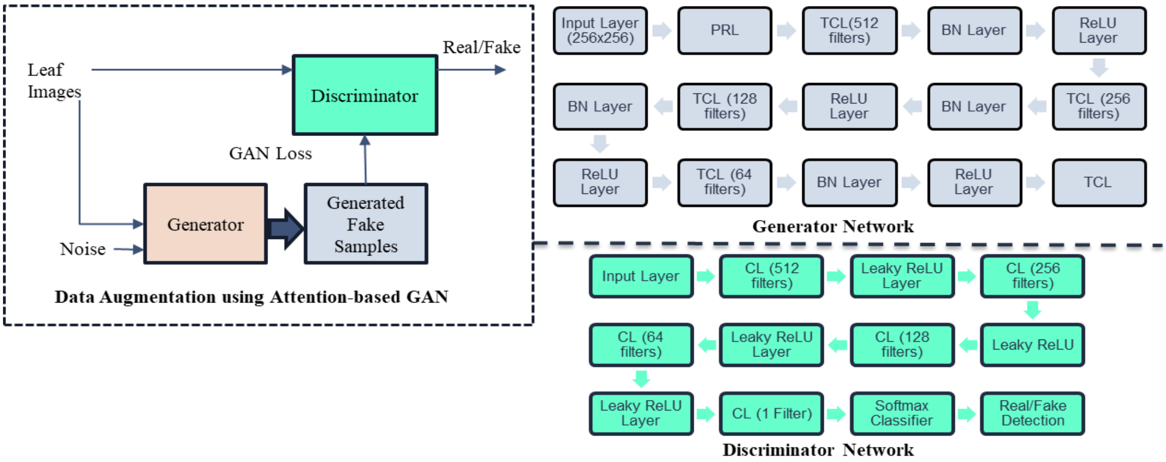


Figure 2. Framework of C-GAN model for data augmentation.

The generator model of C-GAN comprises an input layer, a dense layer, an embedding layer, a leaky ReLU layer, a reshape layer, a concatenate layer, and four convolutional layers, with each layer followed by a leaky ReLU activation. Conversely, the C-GAN discriminator model consists of an input layer, an embedding layer, a dense layer, a reshape layer, a concatenate layer, four convolutional layers followed by leaky ReLU layers, a flattening layer, and a dropout layer.

The generator model (G) generates synthetic images using random noise and latent points, while the discriminator model (D) differentiates between real and fake samples produced by the generator model [23, 42]. The generator model, denoted as G, receives input noise and latent points distributed as $n_z(z)$.. On the other hand, the discriminator model, denoted as D, is provided with image samples and class labels y. The objective of the discriminator model is to improve the probability of correctly assigning class labels to both original and synthetic images, expressed as $logD(im|y)$.

Meanwhile, the generator model aims to minimize the generator loss, which is defined as $\log(1 - \mathrm{D}(\mathrm{G}(\mathrm{z}|\mathrm{y}))$. The overall objective function of the C-GAN, following a min-max approach, is presented in Equation 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 TPDCNN is composed of four parallel DCNN structures, with each arm utilizing different filter dimensions: 3×3, 5×5, 7×7, and 9×9, as given in Figure 3. The use of different filter sizes allows the network to capture both fine and coarse textural information from the leaf images.

Each DCNN arm consists of three 2D convolutional layers (Conv-2D), three rectified linear unit (ReLU) layers, and three maximum pooling layers (MaxPool). After the third MaxPool layer, the resulting feature maps are flattened to convert the multi-dimensional representations into a one-dimensional vector. These flattened features from all four arms are then concatenated and passed to a fully connected layer. In the final layer, a softmax classifier based on probability is employed for classification.

The convolutional layer plays a vital role in capturing the correlation and connectivity between local regions on the plant leaf surface. It describes discriminative attributes such as texture, edges, surface properties, and shape of the plant leaf. In this layer, the input leaf image is convolved with various convolutional filters, generating feature maps that represent distinctive characteristics of the leaf. The ReLU layer applies an activation function that sets all negative values from the convolutional layer output to zero, while preserving non-negative values. This ReLU activation function helps alleviate the vanishing gradient problem, making the CNN features more effective and efficient for training.

It introduces non-linearity to the data, which is easier to optimize. The maximum pooling layer selects the maximum value within a pooling window, enabling the extraction of salient information from the leaf crops and reducing the dimensionality of the feature maps [30, 43-45].

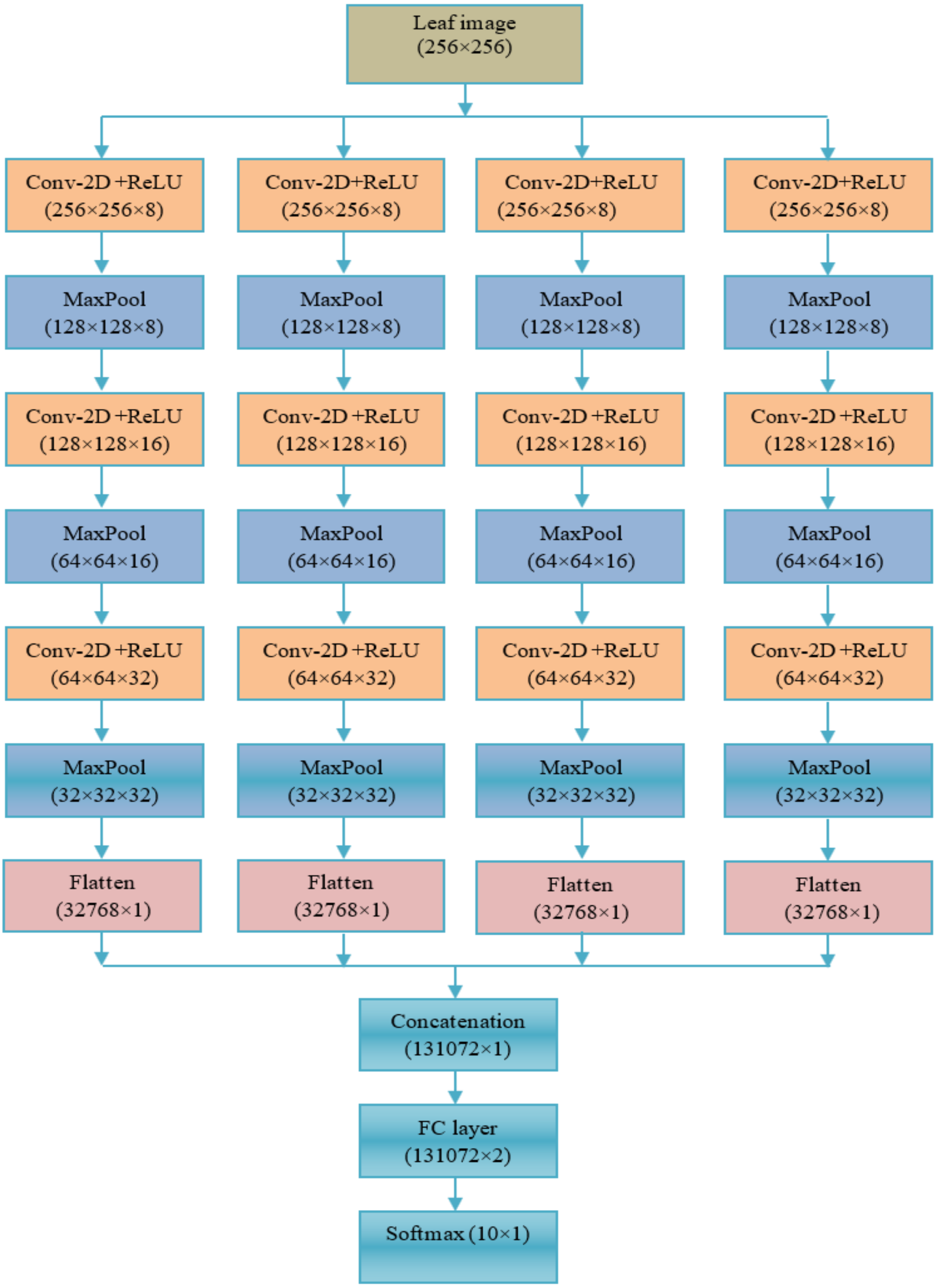


Figure 3. Network architecture of the proposed system.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed system was implemented on an Nvidia GPU with 512 tensor cores and 16 GB RAM.

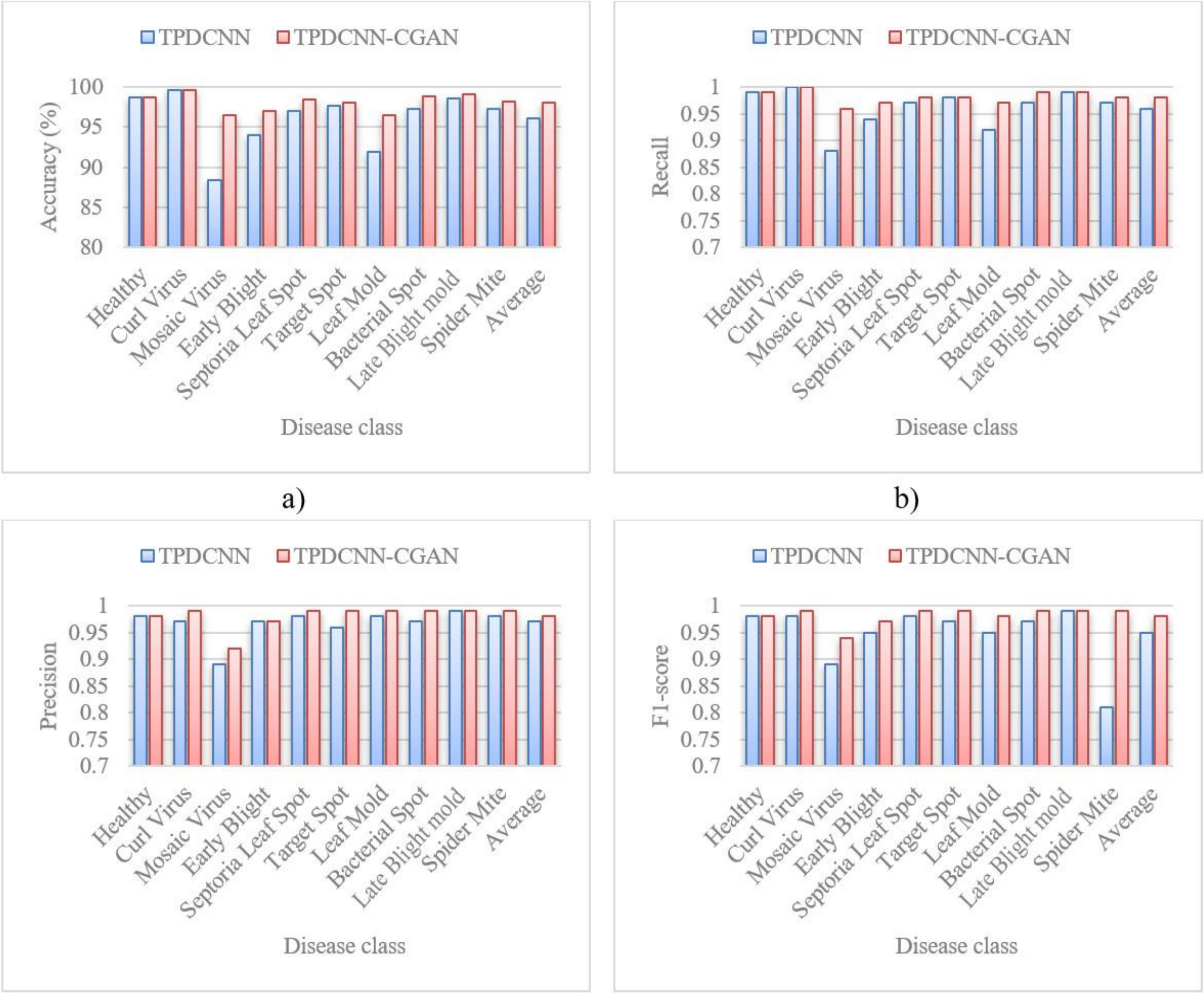
4.1. Performance Evaluation for 10-Class PLDD

Figure 4 presents the results of the proposed TPDCNN model for the 10-class classification of tomato PLDD. When trained on the original dataset, the proposed model achieves higher accuracy for the curl virus (99.58%), healthy (98.74%), and late blight mold (98.60%) classes. However, it exhibits lower disease detection accuracy for the mosaic virus (88.39%) and leaf mold (91.96%) diseases due to the lower number of training samples, which leads to class imbalance issues. For the healthy class, both models achieved identical results with an accuracy of 98.74%, precision of 0.98, recall of 0.99, and an F1-score of 0.98, indicating strong performance even without CGAN. Similarly, for the curl virus class, TPDCNN-CGAN slightly improved over TPDCNN, maintaining an accuracy of 99.58%, but increasing precision to 0.99 compared to 0.97 in TPDCNN, while recall remained perfect at 1.00, producing a higher F1-score of 0.99 compared to 0.98. The mosaic virus class shows the most significant improvement after adding CGAN. TPDCNN's accuracy of 88.39% rises to 96.43% with TPDCNN-CGAN. Precision improves from 0.89 to 0.92, recall from 0.88 to 0.96, and F1-score from 0.89 to 0.94, reflecting better generalization and class differentiation. Likewise, for early blight, TPDCNN's metrics (accuracy 94%, precision 0.97, recall 0.94, F1-score 0.95) increased to 97% across all metrics in TPDCNN-CGAN, indicating more stable detection. For the septoria leaf spot class, TPDCNN achieved 96.99% accuracy, which improved to 98.49% with TPDCNN-CGAN. The precision rose from 0.98 to 0.99, recall from 0.97 to 0.98, and F1-score from 0.98 to 0.99. Similarly, for target spot, the accuracy increased from 97.62% to 98.10%, with precision rising from 0.96 to 0.99, and F1-score from 0.97 to 0.99. These increments show how CGAN enhances robustness in mid-performing classes. The leaf mold class also benefited significantly, where TPDCNN accuracy of 91.96% improved to 96.50%. Precision increased from 0.98 to 0.99, recall from 0.92 to 0.97, and F1-score from 0.95 to 0.98. For bacterial spot, the accuracy rose from 97.34% to 98.90%, with precision, recall, and F1-score all reaching 0.99 with TPDCNN-CGAN compared to 0.97–0.99 ranges in TPDCNN. Classes like late blight mold already performed strongly in TPDCNN, reaching 98.6% accuracy, 0.99 precision and recall, and 0.99 F1-score, which slightly improved to 99.13% accuracy in TPDCNN-CGAN, maintaining the same high precision, recall, and F1-score. However, the spider mite class shows a dramatic jump in F1-score from 0.81 in TPDCNN to 0.99 in TPDCNN-CGAN, with accuracy rising from 97.22% to 98.21%, precision from 0.98 to 0.99, and recall from 0.97 to 0.98, indicating CGAN's effectiveness at handling previously challenging cases. Overall, the average performance across all 10 classes shows TPDCNN-CGAN outperforms TPDCNN in every metric: accuracy improves from 96.04% to 98.11%, precision from 0.97 to 0.98, recall from 0.96 to 0.98, and F1-score from 0.95 to 0.98.

Table 2. Performance of the proposed model for 10-class tomato leaf disease detection.

Leaf disease	TPDCNN				TPDCNN-CGAN			
	Acc	Recall	Precision	F1-score	Acc	Recall	Precision	F1-score
Healthy	98.74	0.99	0.98	0.98	98.74	0.99	0.98	0.98
Mosaic virus	88.39	0.88	0.89	0.89	96.43	0.96	0.92	0.94
Curl virus	99.58	1.00	0.97	0.98	99.58	1.00	0.99	0.99
Spider mite	97.22	0.97	0.98	0.80	98.21	0.98	0.99	0.99
Septoria leaf spot	96.99	0.97	0.98	0.98	98.49	0.98	0.99	0.99
Early blight	94.00	0.94	0.97	0.95	97.00	0.97	0.97	0.97
Leaf mold	91.96	0.92	0.98	0.95	96.50	0.97	0.99	0.98
Target spot	97.62	0.98	0.96	0.97	98.10	0.98	0.99	0.99
Late Blight mold	98.60	0.99	0.99	0.99	99.13	0.99	0.99	0.99
Bacterial spot	97.34	0.97	0.97	0.97	98.90	0.99	0.99	0.99
Average	96.04	0.96	0.97	0.95	98.11	0.98	0.98	0.98

Table 2 presents the class-wise performance of the proposed TPDCNN and TPDCNN-CGAN models for 10-class tomato leaf disease detection. It shows that TPDCNN-CGAN consistently improves accuracy, recall, precision, and F1-score across all disease categories, particularly for Mosaic Virus, Leaf Mold, and Bacterial Spot, where synthetic data generation helps overcome class imbalance.



a)

b)

c)

d)

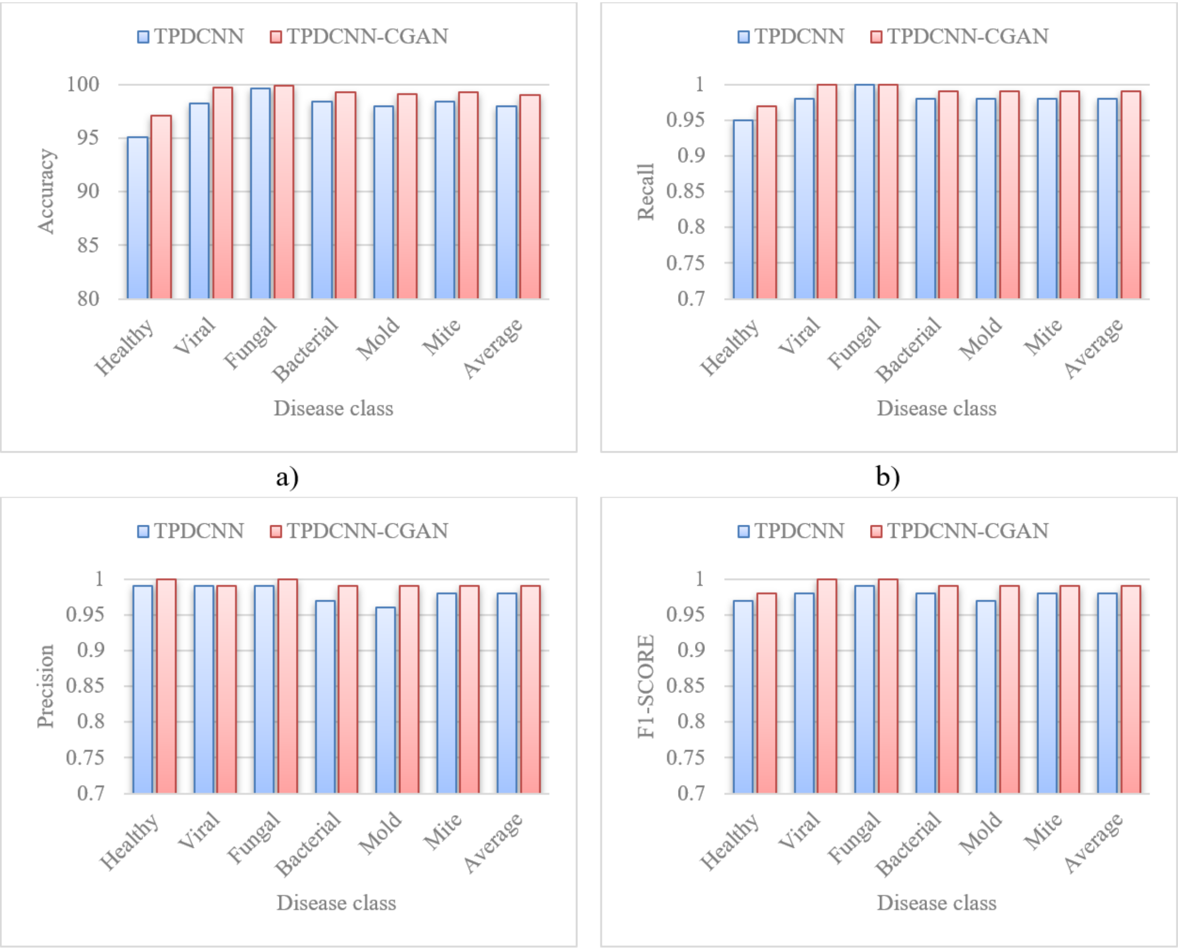
Figure 4. Performance of proposed TPDCNN for 10-class PLDD.

When trained on the augmented dataset (with 2450 samples per class) using data augmentation through C-GAN, the proposed model achieves higher accuracy for the curl virus (99.58%), late blight mold (99.13%), bacterial spot (98.90%), and healthy samples (98.74%). The data augmentation using C-GAN helps address the class imbalance problem and improves the accuracy for the mosaic virus (96.43%) and leaf mold (96.50%) diseases. The proposed TPDCNN-CGAN model achieves a 2.15% improvement in disease detection accuracy over the TPDCNN model without data augmentation for the 10-class disease detection task. The F1-score provides a balanced evaluation of the performance of the 10-class disease detection.

4.2. Performance Evaluation for 6-Class PLDD

Figure 5 presents the outcomes of TPDCNN for the 6-class PLDD, including healthy, viral, bacterial, fungal, mold, and mite diseases. For the Healthy class, TPDCNN achieved 95.1% accuracy, while TPDCNN-CGAN improved it to 97.06%, with precision and recall reaching 1.0 and 0.97, respectively. In the Viral class, the accuracy rose from 98.2% to 99.71%, with the TPDCNN-CGAN attaining a perfect recall and F1-score of 1.0, compared to 0.98 with TPDCNN. For the Fungal class, TPDCNN-CGAN achieved nearly perfect scores with 99.89% accuracy, 1.0 precision, recall, and F1-score, surpassing TPDCNN's 99.59% accuracy and a slightly lower F1-score (0.99). Similarly, for the Bacterial class, accuracy improved from 98.43% to 99.27%, with precision and recall increasing from 0.97–0.98 to 0.99 each. The Mold class also showed a gain from 98% to 99.1% accuracy, and the F1-score improved from 0.97 to 0.99. Finally, in the Mite class, TPDCNN-CGAN recorded 99.27% accuracy compared to 98.41% for

TPDCNN, with higher precision, recall, and F1-score (0.99 vs. 0.98). On average, TPDCNN achieved 97.96% accuracy, 0.98 precision, 0.98 recall, and 0.98 F1-score. In comparison, TPDCNN-CGAN improved these values to 99.05%, 0.99, 0.99, and 0.99, respectively, clearly highlighting the superior generalization and robustness of the CGAN-enhanced approach in tomato leaf disease classification.



a) b)

c) d)

Figure 5. Performance of proposed TPDCNN for 6-class PLDD.

The performance of the suggested TPDCNN and TPDCNN-CGAN models for 6-class tomato leaf disease detection is shown in Table 3. The findings demonstrate that TPDCNN-CGAN consistently outperforms all other categories in terms of accuracy, recall, precision, and F1-score, with considerable gains for the Healthy, Mold, and Mite classes.

Table 3. Performance of the proposed model for 6-class tomato leaf disease detection

Leaf Disease	TPDCNN				TPDCNN-CGAN			
	Acc	Recall	Precision	F1-score	Acc	Recall	Precision	F1-score
Healthy	95.10	0.95	0.99	0.97	97.06	0.97	1.00	0.98
Fungal	99.59	1.00	0.99	0.99	99.89	1.00	1.00	1.00
Viral	98.20	0.98	0.99	0.98	99.71	1.00	0.99	1.00
Mold	98.00	0.98	0.96	0.97	99.10	0.99	0.99	0.99
Mite	98.41	0.98	0.98	0.98	99.27	0.99	0.99	0.99
Bacterial	98.43	0.98	0.97	0.98	99.27	0.99	0.99	0.99
Average	97.96	0.98	0.98	0.98	99.05	0.99	0.99	0.99

4.3. Performance Evaluation for 2-Class PLDD

The performance of the suggested model for two-class tomato leaf disease detection utilizing both the original TPDCNN and the improved TPDCNN-CGAN frameworks is shown in Table 4. The results demonstrate the efficacy of synthetic data creation in enhancing class balance and overall classification reliability, with TPDCNN-CGAN achieving higher accuracy, recall, precision, and F1-score for both the Healthy and Disease classes.

Table 4. Performance of the proposed model for 2-class tomato leaf disease detection.

Leaf disease	**TPDCNN (Healthy-1591, Disease-14423)**				**TPDCNN-CGAN (Healthy-2450, Disease-22050)**			
	Acc	**Recall**	**Precision**	**F1-score**	**Acc**	**Recall**	**Precision**	**F1-score**
Healthy	97.00	0.97	0.97	0.97	98.49	0.98	0.99	0.99
Disease	98.74	0.99	0.98	0.98	99.79	1.00	0.99	0.99
Average	97.87	0.98	0.97	0.98	99.14	0.99	0.99	0.99

The performance of the proposed TPDCNN was further validated for two-class disease detection, consisting of healthy and diseased classes as given in Figure 6. For the Healthy class, TPDCNN achieves an accuracy of 97% with precision, recall, and F1-score all at 0.97, whereas TPDCNN-CGAN raises the accuracy to 98.49%, precision to 0.99, recall to 0.98, and F1-score to 0.99. This shows a notable gain in reliability for detecting healthy leaves. Similarly, for the Disease class, TPDCNN already performs well with 98.74% accuracy, 0.98 precision, 0.99 recall, and 0.98 F1-score. However, TPDCNN-CGAN further improves accuracy to 99.79%, precision and F1-score to 0.99, and achieves a perfect 1.00 recall, indicating it identifies diseased leaves almost flawlessly. Overall, TPDCNN yields 97.87% accuracy, 0.97 precision, 0.98 recall, and 0.98 F1-score. These values rise to 99.14% accuracy, 0.99 precision, 0.99 recall, and 0.99 F1-score with TPDCNN-CGAN, reflecting a consistent and substantial improvement.

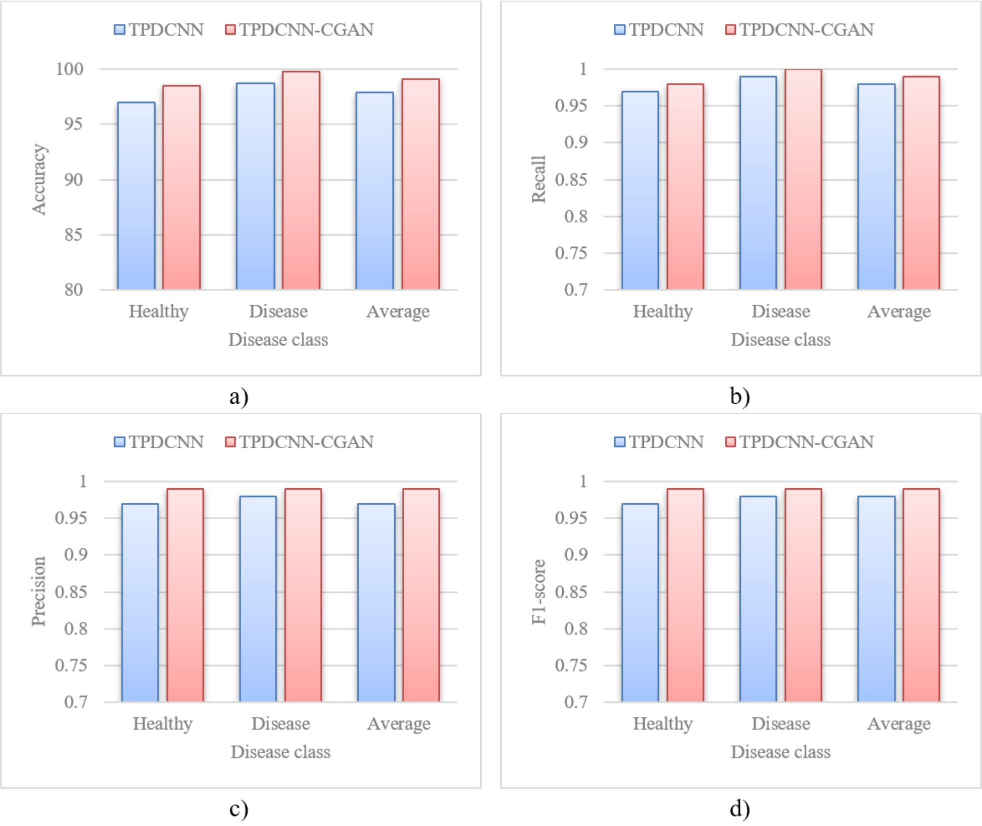


Figure 6. Performance of the proposed TPDCNN for 2-class PLDD.

4.4. Experimental Results on Real-Time Dataset

We have evaluated the effectiveness of the TPDCNN for the 2-class classification (healthy and diseased) of tomato leaf disease detection, considering 2000 images per class. The TPDCNN achieves an overall accuracy of 97.50% for TPDCNN+GAN and 95.405% for TPDCNN. It provides reliable and efficient results for real-time images for a system trained using the PlantVillage dataset.

4.5. Discussions on Overall Results

The performance of the TPDCNN model was assessed by varying the number of parallel DCNN layers in the architecture as given in Figure 7. Specifically, the outcomes were evaluated for one, two, and three parallel DCNN layers. For the 2-class model, accuracy steadily rises from 84.5% to 97.3% with increasing parallel layers in CPDCNN, while C-GAN+CPDCNN consistently outperforms it, reaching 98.74% at four layers. For the more challenging 6-class model, CPDCNN improves from 82.3% to 90.5% as layers increase, but the C-GAN-enhanced version jumps from 88.2% to 96.4%, a larger gain at every depth. Similarly, in the 9-class model, CPDCNN progresses from 89.3% to 96.4%, whereas C-GAN+CPDCNN achieves 92.7% to 98.41%, consistently higher.

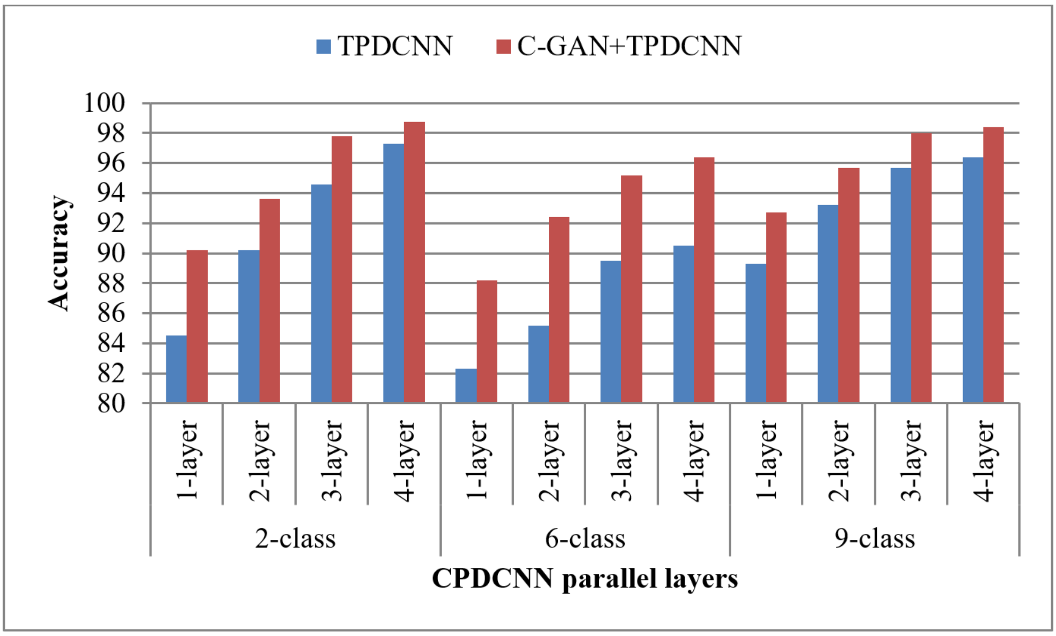


Figure 7. Accuracy of the proposed model for different parallel arms in TPDCNN (2, 6, and 9-class classification).

The training time and recognition time for the TPDCNN, as well as the implementation of the preceding methods, are shown in Table 5. The TPDCNN had significantly fewer trainable parameters compared to other methods. It only required 122,882, 155,654, and 188,426 trainable parameters for 2-class, 6-class, and 10-class tomato PLDD, respectively. However, the ResNet and DenseNet121 require 11.8 million and 8 million trainable parameters, resulting in higher system complexity. This reduction in trainable parameters contributed to minimizing the computational complexity of the network. It also increased the feasibility of implementing the proposed system on portable, standalone devices in the future, as it requires fewer resources. In comparison to ToLeD (3645 seconds), ResNet (3276 seconds), and C-GAN + DenseNet121 (2867 seconds), the lightweight TPDCNN proposed here takes a shorter training time, approximately 2564 seconds. The average recognition time for the TPDCNN is 0.345 seconds, much faster than C-GAN + DenseNet121, which takes 0.765 seconds, ResNet, which takes 0.867 seconds, and ToLeD, which takes 1.2 seconds.

Table 5. Training and recognition times of the systems for 10-class PLDD.

Method	Training time	Recognition time	Trainable parameters
ToLeD [15]	3645 sec	1.2 sec	-
ResNet [16]	3276 sec	0.867 sec	~11.8 M
C-GAN + DenseNet121 [17]	2867 sec	0.765 sec	~8 M
Suggested TPDCNN	2564 sec	0.345 sec	188426

The effectiveness of the proposed TPDCNN-based PLDD system was compared to traditional state-of-the-art methods for PLDD, as presented in Table 6. The TPDCNN achieved superior results, with an accuracy of 99.14% and 97.87% for 2-class disease detection with and without data augmentation, respectively. In comparison, ResNet achieved an accuracy of 97.28% for the tomato class [16]. For 10-class disease detection, the TPDCNN achieved an accuracy of 98.11% with data augmentation and 96.04% without data augmentation. It also achieved accuracies of 99.05% and 97.96% for the 6-class PLDD. The proposed TPDCNN model outperformed other methods, showing a 7.57% improvement over ToLeD [15] and a 1.02% improvement over DenseNet121 [17] for 10-class tomato PLDD. The parallel architecture of TPDCNN facilitated better connectivity between local and global features in plant leaf images, enhancing the discriminative capability of detecting defective areas on the leaf surface.

Table 6. Performance comparison with traditional techniques (PlantVillage - Tomato).

Author and year	Method	Number of classes	Performance			
			F1-score	Precision	Recall	Accuracy
Moussafir, et al. [15]	ToLeD	10	0.91	0.90	0.92	91.20%
Adhikari, et al. [16]	ResNet with SGD optimization	2	-	-	-	97.28%
Karthik, et al. [17]	C-GAN + DenseNet121	5	0.99	0.99	0.99	99.51%
		7	0.98	0.98	0.99	98.65%
		10	0.97	0.97	0.97	97.11%
Proposed method	TPDCNN	2	0.98	0.97	0.98	97.87%
		6	0.98	0.98	0.98	97.96%
		10	0.95	0.97	0.96	96.04%
	TPDCNN-CGAN	2	0.99	0.99	0.99	99.14%
		6	0.99	0.99	0.99	99.05%
		10	0.98	0.98	0.98	98.11%

5. CONCLUSIONS AND FUTURE SCOPE

This article investigates a lightweight parallel DCNN approach for detecting tomato plant leaf diseases, enhancing feature distinctiveness and addressing the problem of filter size selection. The proposed model demonstrates the capability to detect even minor diseases on leaf samples. Additionally, a C-GAN is effectively implemented for synthetic image generation, which helps mitigate the class imbalance problem resulting from the uneven distribution of samples in the training dataset. The proposed TPDCNN achieves high accuracies of 99.14%, 99.05%, and 98.11% for 2-class, 6-class, and 10-class disease detection, respectively, using the Tomato PlantVillage dataset. Furthermore, the TPDCNN-CGAN model improves disease detection accuracy by 2.15% compared to the TPDCNN without data augmentation for the 10-class disease detection task. These results indicate that the proposed model outperforms traditional state-of-the-art methods for tomato PLDD.

The "explainability and interpretability" of the TPDCNN are limited due to the black-box nature of the DL framework. The effectiveness is challenging due to extensive hyperparameter tuning of the TPDCNN. In the future, the "Explainability and Interpretability" of the system can be improved by inculcating explainable AI (XAI) to enhance system trust.

The TPDCNN performance can be improved by optimizing the algorithm's hyperparameters. Additionally, the proposed network can be extended by increasing its depth and applied to detect leaf diseases in multiple plant species, offering a versatile solution for plant disease detection.

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