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# Management of Crop Diseases through Deep Convolutional Neural Network-Based Leaf Disease Detection

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**Abstract**

The effective management of crop leaf disease detection (CLDD) is greatly facilitated by automatic identification techniques, which have become increasingly important in agriculture. Currently, deep learning is a prominent area of research that can help manage and address the challenges faced by farmers. This paper proposes a Deep Convolutional Neural Network (DCNN) approach to manage and improve the accuracy of crop leaf disease detection. Additionally, the proposed algorithm incorporates data augmentation techniques to manage data scarcity issues arising from uneven dataset sizes. The performance of the proposed strategy is evaluated on the PlantVillage dataset for tomato plants, focusing on metrics such as accuracy, precision, recall, and F1-score, demonstrating effective management of crop disease detection. The results show significant improvements over traditional methods, highlighting the effectiveness of the proposed approach in managing crop leaf diseases.

**Keywords:** CLDD, Deep Learning, Smart Agriculture, CNN, AlexNet.

## I. Introduction

In India, agriculture is spread over a very large area. So, about 70% of the economy is dependent on agriculture. The growth of any developing country in the Asian region normally depends upon the growth of the agricultural field. Environmental changes such as continuously changing climate, temperature, and pollution affect the crop yield, which causes loss of farmers as well as the nation [1-3]. The disease in the crop diminished the quality of product developed using crop material and also degrades the quality of the food obtained from the particular crop. Various crop diseases are generated due to bacterial, fungal, or environmental reasons such as early blight (EB), late blight (LB), mosaic virus (MV), dark spot (DS), curl virus (CV), etc. Therefore, it is essential to detect the defects to improve the crop quality and avoid future economic disasters [3-8].

Currently, the crop diseases whose accuracy are low and are found less reliable are diagnosed manually. The consequence of the manual leaf disease detection is highly sensitive to the human expert's knowledge, erroneous due to vision problems, less rate of fatigue and tiredness, and wastage of manpower. Thus, in the last decade, various computer vision-based techniques utilizing machine learning (ML) and deep learning (DL) have been adopted for crop leaf disease detection. The outcomes of the traditional machine learning-based CLDD depend upon the type, length, and variability of the crop leaf features [9-10, 24]. Kulkarni et al. [11] have presented plant leaf disease detection based on the Gabor filter and artificial neural network (ANN). They got 91% accuracy for the BDD, Alternaria, and Anthracnose disease detection. Arivazhagan et al. [12] have developed a software solution, which automatically detects the signs of diseases immediately when they seem on plant leaves. They got 94% accuracy for disease detection. Tripathi et al. [13] have used two techniques for the detection of leaf disease which are Neural Networks and Image processing. They also used a K-mean clustering algorithm to divide images for the identification of infected areas of leaves. Pooja V et al. [14] have presented CLDD based on ML mechanisms and image processing tools and used Support Vector Machine (SVM) to obtain results. Singh et al. [15] have presented an automatic leaf disease detection using Image processing to help the farmers in the early detection of disease and provide useful information to control the disease. They have offered the system which currently detects the disease in plant leaves of Pharsalus Vulgaris (Beans) and Camellia assamica (Tea). Delaware et al. [16] have offered an disease detection approach, which recognizes the healthiness of plant leaves using an Image processing technique. Alom et al. [17] have presented a brief survey on the advancement occurring in the DL, starting with the DNN. Hang et al. [18] have presented a system to detect a disease based on DNN. They obtained better performance and achieved 91.7% accuracy.

The ML algorithms provide poor results for the lower dataset and tend to overfit for the high amount of dataset. The feature selection algorithm is a complicated task because of the availability of numerous color, texture, and shape-based descriptors to characterize the leaf features. The deep learning techniques have been widely used because of their higher feature distinguishing capability, hidden feature extraction nature, and inbuilt combination of feature characterization and classification. However, the consequences of these techniques is often limited because of the extensive hyper-parameter tuning, larger training and testing time, complex architecture and a large number of trainable parameters.

This paper presents crop leaf disease detection based on a deep convolutional neural network (DCNN). The major contributions of the offered work are summarized as follows:

- Implementation of lightweight DCNN to improve the feature distinctiveness of the leaf image to improve the CLDD performance.
- Implementation of data augmentation to minimize the data scarcity problem arises due to uneven samples in the training dataset.
- To estimate the outcomes of the offered CLDD approach based on various evaluation metrics such as accuracy, precision, recall, and F1-score.

The rest of the paper is structured as follows: Section II provides a detailed description of the offered CLDD approach based on DCNN. Section III gives extensive experimentation and discussion on the results. Lastly, section IV depicts the conclusion and future direction for the extension of work for future improvement.

## II. Offered Strategyology

The workflow of the offered CLDD system is shown in Fig. 1. The offered DCNN architecture consists of three layers of the CNN where each CNN layer encompasses convolution (Conv), Rectified linear unit (ReLU), and maximum pooling layer (MaxPool).

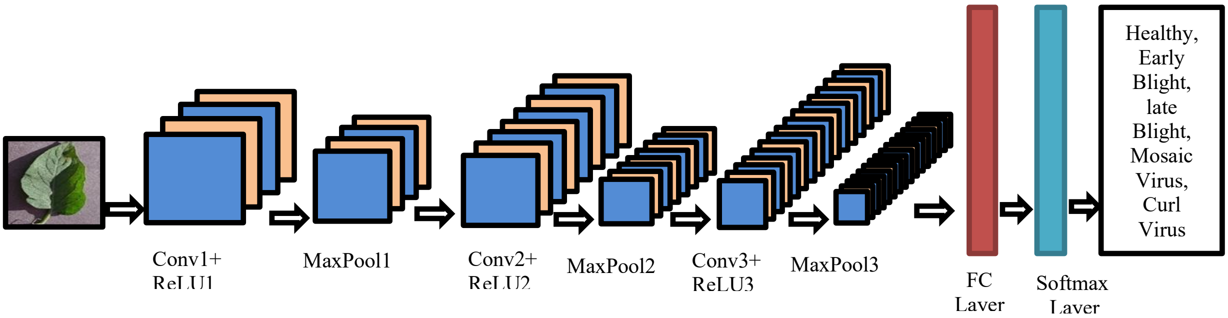
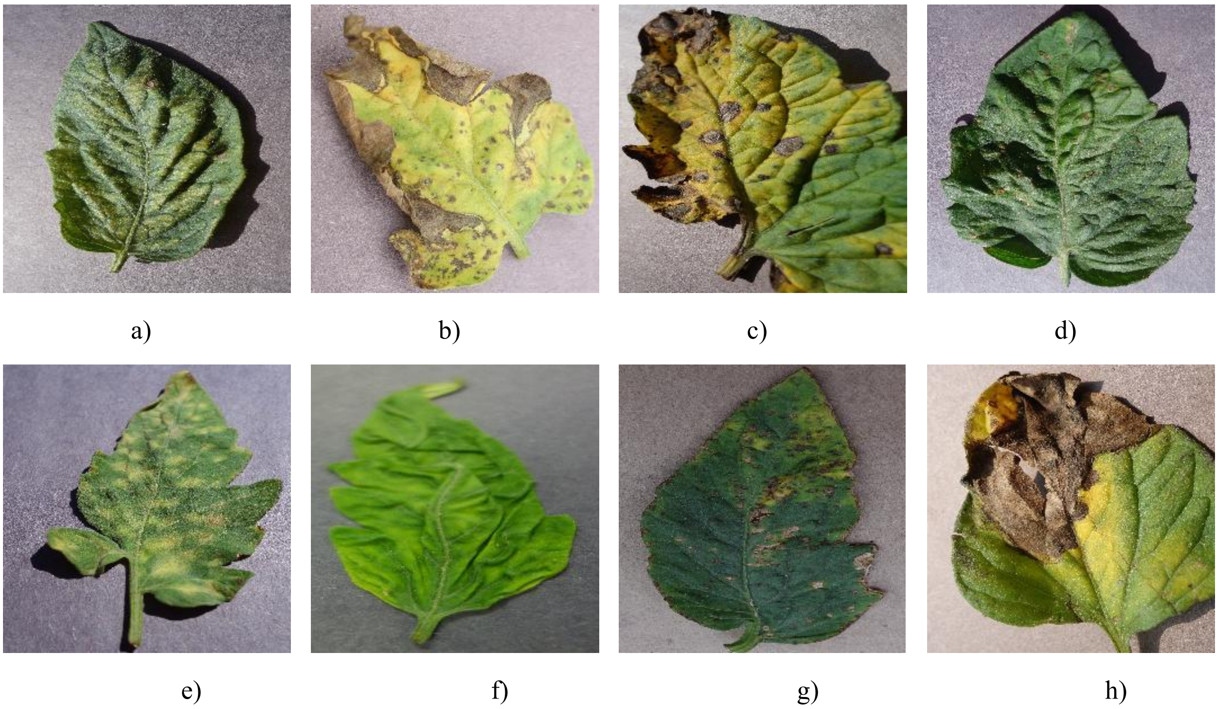



**Fig. 1 Architecture of offered CLDD using DCNN**

### 2.1 Dataset and Data Augmentation

The consequence of the offered system is analyzed on the tomato plant of the PlantVilalge dataset [19]. The tomato plant dataset consists of the images of the nine leaf diseases such as bacterial spot, early blight, late blight, healthy, curl virus, target spot, spider mite, septoria leaf spot, and leaf mold as given in Table 1. The sample images of the tomato leaf diseases are shown in Fig. 2.

The original dataset consists of the uneven dataset size which often leads to the data imbalance problem and provides poor accuracy for the disease class having low training samples. The dataset consists of a minimum of 952 samples for the leaf mold disease type and a maximum of 3209 samples for the curl virus. Therefore, all other classes are augmented to the 3200 samples per class except the curl virus class. out of the available dataset, 70% and 305 data samples are considered for the training and testing purpose. the augmented samples are created by translating the image's five pixels vertically and five pixels horizontally and by rotating the images by 20 degrees.



a) b) c) d)

e) f) g) h)

**Figure 2. Samples of tomato plant a) Spider mite b) Septoria leaf spot c) Early Blight d) Target spot e) Leaf mold f) Curl spot g) Bacterial spot h) Late blight**

### 2.2 Deep Convolutional Neural Network

The offered DCNN consists of the lightweight architecture with the three CNN layers. The convolution layer helps to find the deep features of the image. It provides the better connectivity between local and global features of the image. The offered architecture includes 36, 128 and 256 filter for first, second and third convolution layer respectively. The filter kernel with the dimensions of 3×3 pixels are used for the convolution. The convolution operation is carried out by considering stride of one pixel and zero padding. Further, the ReLU layer is used to improve the non-linearity of the signal. It replaces the negative values with the zero that aids to fasten the training process as well. The maximum pooling layer helps to select the important features from the ReLU layer. It also minimize the feature dimensions. The fully connected layer connects every neuron with each other to improve the connectivity of the features. Finally, softmax classifier is used for the classification of crop disease. The offered DCNN is trained using mini-batch gradient descent optimization algorithm with the learning rate of 0.001 and batch size of the 64.

## III. Experimental Results

The offered system is implemented using Python on the personal computer, which has a core i3 processor with 2.4GHz speed, and 8GB RAM on the windows10 operating system. The outcomes of the offered DCNN-based CLDD are described in Table 2.

**Table 2: consequence of offered system with and without data augmentation (Tomato plant)**

| Leaf Disease | Without Data Augmentation | | | | With Data Augmentation | | | |
|---|---|---|---|---|---|---|---|---|
| | Acc | Recall | Precision | F1-score | Acc | Recall | Precision | F1-score |
| Bacterial Spot | 98.59 | 0.99 | 0.97 | 0.98 | 99.06 | 0.99 | 0.97 | 0.98 |
| Curl Virus | 99.07 | 0.99 | 0.94 | 0.96 | 99.07 | 0.99 | 0.97 | 0.98 |
| Early Blight | 94.67 | 0.95 | 0.98 | 0.96 | 96.00 | 0.96 | 0.99 | 0.97 |
| Healthy | 96.65 | 0.97 | 0.97 | 0.97 | 96.65 | 0.97 | 0.98 | 0.97 |
| Late Blight | 98.08 | 0.98 | 0.98 | 0.98 | 98.08 | 0.98 | 0.99 | 0.98 |
| Leaf Mold | 94.01 | 0.94 | 0.96 | 0.95 | 95.45 | 0.95 | 0.96 | 0.96 |
| Septoria Leaf Spot | 96.42 | 0.96 | 0.97 | 0.97 | 96.42 | 0.96 | 0.98 | 0.97 |
| Spider Mite | 94.04 | 0.94 | 0.98 | 0.96 | 97.22 | 0.97 | 0.97 | 0.97 |
| Target Spot | 93.59 | 0.94 | 0.98 | 0.96 | 98.10 | 0.98 | 0.98 | 0.98 |
| Average | 96.12 | 0.96 | 0.97 | 0.97 | 97.34 | 0.97 | 0.98 | 0.98 |

The offered strategy provides an accuracy of 96.12%, recall rate of 0.96, precision of 0.97 and F1-score of 0.97 for the DCNN without data augmentation. Whereas, it provides an accuracy of 97.34%, recall rate of 0.97, the precision of 0.98 and F1-score of 0.98 for the DCNN with data augmentation. The data augmentation helps to minimize the class imbalance problem and gives 1.26% improvement over the DCNN without data augmentation. the accuracy of the DCNN with data augmentation lies in between 95.45% (leaf mold) and 99.07% (curl virus).

**Table 3: Comparative analysis of offered Strategy**

| Strategys | Accuracy |
|---|---|
| Gabor Transform + ANN [11] | 91.00% |
| Texture Features [12] | 94% |
| Machine Learning + Image processing tools [14] | 92.4% |
| Offered Strategy | 97.34% |

The performance comparison with the previous state if arts suggests that the offered strategy provides better results for the augmented dataset as given in table 3. It provides an accuracy of 97.34% for tomato leaf disease detection.

## IV. Conclusion

Thus, the article presents crop leaf disease detection based on the simple and lightweight deep convolutional neural network. It provides the higher feature variance, larger connectivity between the local and global features of the leaf image. The offered scheme's performance id validated on the PlantVillage dataset using various qualitative and quantitative performance metrics. The offered strategy provides an accuracy of 97.34%, recall rate of 0.97, precision of 0.98 and F1-score of 0.98 for the DCNN with data augmentation. The performance comparison shows the offered approach provides the less complex solution for the crop leaf disease detection compared with the traditional state of arts utilized for the crop disease detection. In future, the strategy can be extended to provide the generalized solution of multiple crop disease detection and minimization in the complexity of the hyper-parameter tuning.

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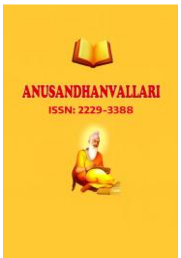




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