Automatic Plant Disease Detection System Using Advanced Convolutional Neural Network-Based Algorithm

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***Abstract*—With technology innovations such as Artificial Intelligence (AI) and Internet of Things (IoT), unprecedented applications and solutions to real world problems are made possible. Precision agriculture is one such problem which is aimed at technology driven agriculture. So far, the research on agriculture and usage of technologies are at government level to reap benefits of technologies in crop yield prediction and finding the cultivated areas. However, the fruits of technologies could not reach farmers. Farmers still suffer from plenty of problems such as natural calamities, reduction in crop yield, high expenditure and lack of technical support. Plant diseases is an important problem faced by farmers as they could not find diseases early. There is need for early plant disease detection in agriculture. From the related works, it is known that deep learning techniques like Convolutional Neural Network (CNN) is best used to process image data to solve real world problems. However, as one size does not fit all, CNN cannot solve all problems without exploiting its layers based on the problem in hand. Towards this end, we designed an automatic plant disease detection system by proposing an advanced CNN model. We proposed an algorithm known as Advanced CNN for Plant Disease Detection (ACNN-PDD) to realize the proposed system. Our system is evaluated with PlantVillage, a benchmark dataset for crop disease detection result, and real-time dataset (captured from live agricultural fields). The investigational outcomes showed the utility of the proposed system. The proposed advanced CNN based model ACNN-PDD achieve 96.83% accuracy which is higher than many existing models. Thus our system can be integrated with precision agriculture infrastructure to enable farmers to detect plant diseases early.**

Keywords*—*Plant disease detection; advanced CNN; Artificial Intelligence (AI); deep learning; precision agriculture

I. Introduction

Agricultural sector in the world is crucial for growing food required by humanity. This field makes the highest contribution towards food and the economy as well. Farmers spend their lives in agricultural activities and work hard in production of different food items besides other commercial products like cotton. However, farmers are suffering from high expenditure involved in cultivation and also plant diseases. Particularly certain crop diseases lead to significant losses to farmers leading to crisis in agricultural domain [1]. Technology innovations such as AI are shaping unprecedented solutions in different real world applications. ML and DL techniques could improve state of the art in solving problems [2]. However, technological innovations in several countries are helping governments and organizations but actual benefits of technologies could not reach farmers. In other words, in spite of innovations in agriculture, technology benefits are not really changing the lives of farmers. To state it differently, at the farmer level the technologies are not exploited. In this paper, our endeavour is to build a system that helps farmers to have automatic detection of plant diseases in a user-friendly fashion.

There are many existing methods dealing with the problem of automatic plant disease detection. PlantVillage [26] is the dataset widely used to have machine learning based approaches for disease detection. An excerpt from the dataset is shown in Fig. 1 reflecting some healthy leaves and diseased ones. Many of the existing methods such as [3], [5], [16] and [21] are based on CNN model. Sardogan *et al*. [3] proposed a hybrid DL technique using CNN and quantization to detect diseases in Tomato crop. Marzougui *et al*. [5] used ResNet model along with data augmentation for automatic disease detection. Hassan *et al*. [16] used pre-trained techniques like InceptionV3 and MobileNet with transfer learning to improve prediction performance. Suma [21] proposed as system for disease prediction and also incorporated a provision to give suitable recommendations on detection of specific crop disease. Andrew *et al*. [25] used models such as Inception v4, VGG16, ResNet50 and DenseNet121 to deal with automatic leaf disease detection process more efficiently. From the review of related works, it is ascertained that most of the existing models are built on CNN. Nevertheless, there is necessity for improving accuracy further and also work with live data collected from agricultural fields. Here are important contributions of the paper.

1) We designed an automatic plant disease detection system by proposing an advanced CNN model.

2) We proposed an algorithm known as Advanced CNN for Plant Disease Detection (ACNN-PDD) to realize the proposed system.

3) Our system is evaluated with PlantVillage [26], a benchmark dataset for crop disease detection result, and real-time dataset (captured from live agricultural fields).

4) The experimental results showed the utility of the proposed system. The proposed advanced CNN model

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ACNN-PDD achieve 96.83% accuracy which is higher than many prior models.

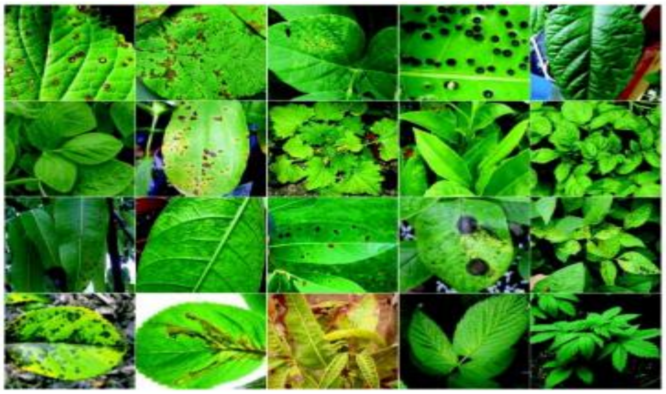

Fig. 1. Leaf samples from plantvillage dataset.

The rest of the paper covers more details of our research. Prior works are reviewed in Section II. Preliminaries is given in Section III while Section IV throws light on the materials and methods associated with our work. Our investigational observations are provided in Section V. Our research is concluded in Section VI.

II. RELATED WORK

This section analyses related works on deep learning based methods for plant disease detection. Ferentinos et al. [1] used many variants of CNN models for disease prediction. They opined that CNN based models are widely used and they are more suitable for image analysis. It is found that various CNN variants are available for processing imagery data. Shruthi et al. [2] reviewed many DL models used for plant disease diagnosis. Their research showed that CNN is the preferred deep learning model. The rationale behind this is that, CNN has power to have discrimination towards efficient predictions. Sardogan et al. [3] defined a hybrid deep learning model using CNN and LVQ to detect diseases in Tomato crop. They found that when LVQ is combined with CNN, it could perform better in disease detection. Kumar et al. [4] explored region based approaches based on CNN models. Their methodology includes feature selection prior to using a supervised learning approach. With region approach, they found that there is increased probability in accurate predictions. Marzougui et al. [5] used ResNet model along with data augmentation for automatic disease detection. It is observed that the ResNet is a model that has provision towards transfer learning leading to better performance. Mishra et al. [6] used Corn crop for disease detection using CNN based model deployed into Raspberry Pi. They could test leaf images collected through mobile phone camera. Thus their system is found to be useful in collecting new samples and detect diseases. Chowdhury et al. [7] used U-Net model for segmentation process while EfficientNet model is used for automatic disease classification. The usage of dual models in their research they found that division of labour led to improved performance. Militante et al. [8] designed a DL based system for disease detection considering agricultural crops. They explored an image pre-processing method for performance enhancement. It is observed that DL modes are better used for image data analytics.

Kannan et al. [9] defined a CNN based methodology along with data augmentation to improve disease detection process using Tomato crop. They also used transfer learning with ResNet50 model and found its utility. With such reuse in the model has improved chances of accuracy in predictions. Gui et al. [10] used background replacement technique along with an improved CNN for disease recognition using uncontrolled field conditions and controlled laboratory conditions. With the mixture of field conditions, the evaluation of the models became more comprehensive. Kumar et al. [11] investigated on Coffee plants using a CNN based architecture for disease detection. Their study revealed the utility of DL models for solving problems in agriculture. Tugrul et al. [12] followed a systematic review approach to explored different CNN variants. Their investigation has resulted in set of CNN variants and their modus operandi besides capability in predictions. Yan et al. [13] proposed an improved CNN model detect diseases such as cedar rust, frogeye spot and scab using Apple leaves. Apart from this, they used several pre-trained models such as VGG16 as well. Their inception model is found to have better performance. When compared with baseline models, their model was performing better significantly. Gajjar et al. [14] incorporated a trained CNN model into an embedded system in order to have automatic detection of leaf diseases. Their ideal of having an embedded system is to provide a solution in hand-held devices. Zeng and Li [15] proposed a method based on CNN by improving it using self-attention in the form of BaseNet architecture. This architecture is found better than its counterparts devoid of self-attention mechanism. Hassan et al. [16] used advanced models like InceptionV3 and MobileNet with transfer learning to improve prediction performance. Their findings are important towards making comparison between baselines and their models. Lu et al. [17] made a review on CNN models for leaf disease detection. Their findings are in affirmative on the capability of CNN in agricultural research. Raina and Gupta [18] studied many models used for disease detection in agricultural crops. Those models could establish the significance of learning based approach to solve problems in agriculture. Ahmad et al. [19] combined stepwise transfer learning and CNN models on imbalanced datasets for disease detection. This research could throw light on dealing with datasets that exhibit imbalance. Panchal et al. [20] investigated on different deep models for image based disease prediction. Their findings revealed that deep models have better opportunities in learning and prediction procedures.

Suma [21] proposed a system for disease prediction and also incorporated a provision to give suitable recommendations on detection of specific crop disease. Such recommendations provide another layer of knowledge to farmer community. Venkataramanan et al. [22] used YOLOv3 technique to obtain leaf from given image. Then that leaf is subjected to a learned CNN model for disease detection. Learning based approach is thus found to be scalable and more useful. Li et al. [23] explored different techniques used for disease detection. Their research has come up with several insights, challenges and current trends in leaf disease detection. Their work insights could trigger further research in the area of disease prediction. Nagasubramanian et al. [24] used hyperspectral imagery for their research. Moreover, they incorporated explainable 3D learning into their methodology for disease identification. Andrew et al. [25] used pre-trained models such as Inception v4, VGG16, ResNet50 and DenseNet121 to deal with automatic leaf disease detection process more efficiently. From the review of related works, it is ascertained that most of the prior models are based on CNN [29]. Nevertheless, there is necessity for improving accuracy further and also work with live data collected from agricultural fields.

III. Preliminaries

DL is a neural networks based advanced ML meant for improving learning process and accuracy in solving real world problems. CNN is a DL technique widely used for image analysis. CNN has multiple layers as presented in Fig. 2.

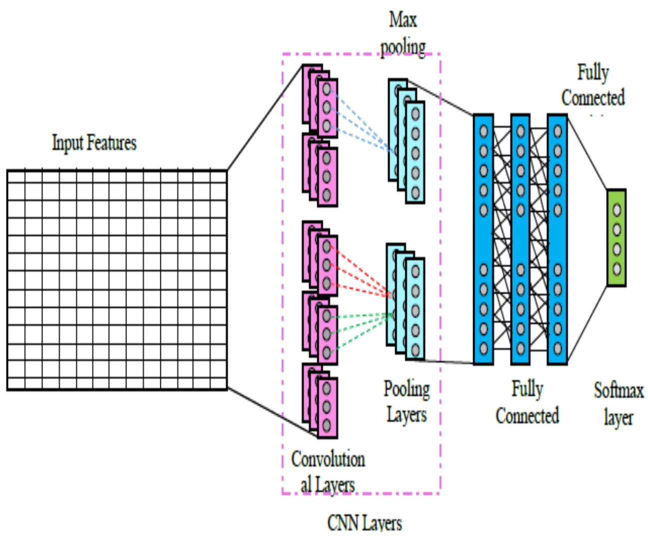

Fig. 2. Overview of baseline CNN architecture.

From the given image, convolutional layers are designed to extract features through correlation of local information. Pooling layers on the other hand perform sub-sampling and reduce feature space. A fully connected layer exploits the outcome of the convolutional and pooling layers and enables the prediction of class labels, while the soft max layer is meant for producing the final output in terms of different classes.

The convolution process is illustrated in Fig. 3. It places a kernel on input and gets pixel values. Then the pixel values are multiplied with kernel values. The result is summarized besides adding bias. The pooling is CNN can be of two types such as max pooling and average pooling as illustrated in Fig. 4. Max pooling is the process of dividing image into many regions and get max value for each region. Whereas average pooling does the same but takes average of each region. Generally, convolution and pooling layers are used in CNN architectures. In the fully connected layer, there is integration of multi-dimensional features and converting them into one-dimensional features eventually.

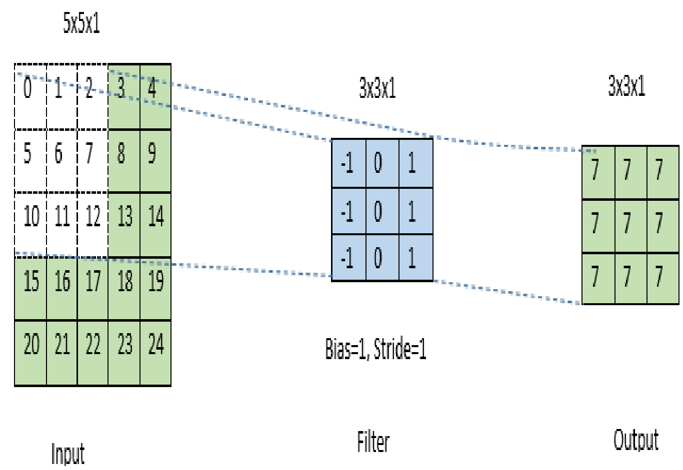

Fig. 3. Illustrates convolution process involved in CNN model.

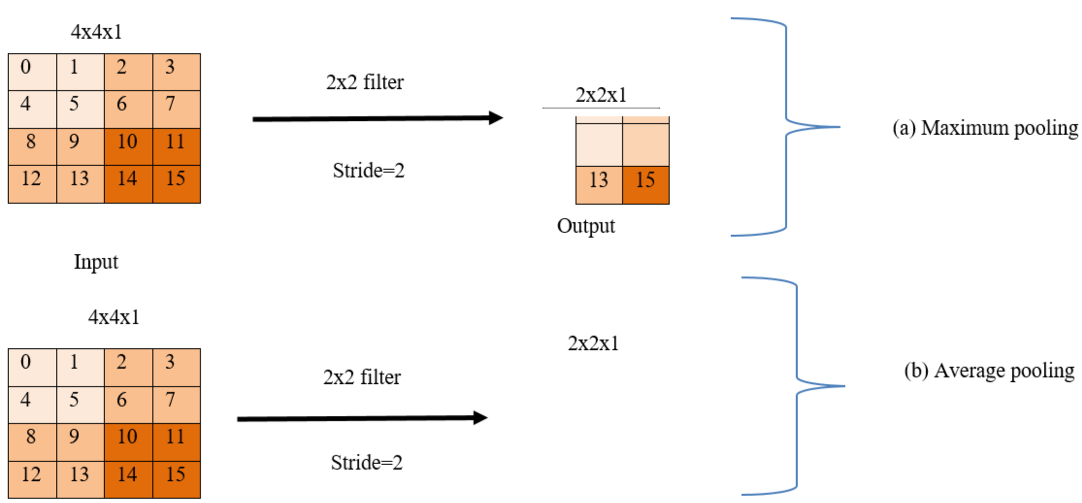

Fig. 4. Illustrates max pooling (a) and Average pooling (b) Operations of a CNN model.

IV. Proposed System

This research proposed an automatic plant disease detection system using DL approach. Towards this end, we considered the base line CNN model described in Section III and improved it to have advanced CNN model. With empirical study, we made different configurations of the layers to be more suitable for the purpose. As presented in Fig. 5, the proposed system is based on learning based phenomena. The proposed advanced CNN model is used to train the system. In other words, our CNN model learns from given training images and labels taken from PlantVillage dataset. We preferred CNN model for our research for many reasons. CNN is found to be most suitable for analysing image content. Its convolutional layers are designed to extract feature maps that reflect the underlying content of images. Moreover, the CNN model's pooling layers are designed to optimize feature maps so as to reduce in size without compromising the discriminative capabilities. CNN has capability to extract features without human intervention [26]. The configuration of CNN is designed such that its computational complexity is relatively less than other deep learning models. Strength of CNN lies in its ability to solve the problem known as "curse of dimensionality" in image data analytics. Its dense nature of the network has its influence in improving accuracy in prediction process [27]. Adjustment of filters in different layers of CNN has its impact on influencing accuracy. Adjustment of kernel size and stride can improve performance of CNN model.

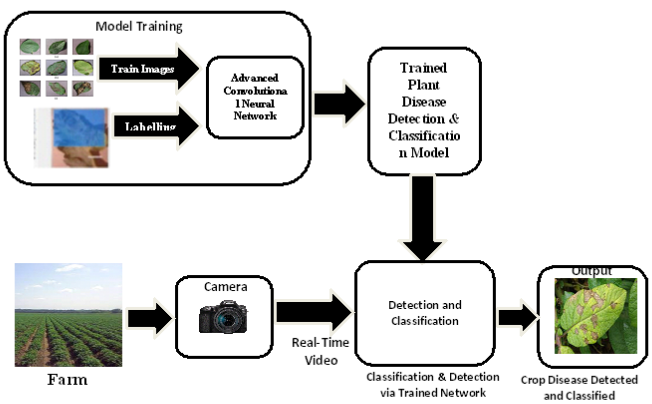

Fig. 5. Proposed automatic plant disease detection system.

The proposed advanced CNN model training set images and also corresponding ground truth. With the given inputs, the CNN model is trained to gain the knowledge pertaining to crop disease detection. After the training process, the learned CNN model has capability to discriminate healthy samples from the ones affected with diseases. In the process of training, convolutional layers are meant for collecting feature maps and pooling layers are meant for optimization of feature maps. The optimized feature maps play an important role in ascertaining knowledge about training samples along with their ground truth. The ground truth of training and testing samples play crucial role in evaluation of the proposed system. Then the knowledge model created is saved to persistent storage for using it later in the plant disease detection process [28]. The proposed system supports readily available test (unlabelled) images from PlantVillage dataset and also real time images captured live from agricultural field using a camera. When a new image is given to the trained model, it is able to detect disease and classify it. In fact, the ability to detect any newly collected test sample is the important characteristic of the proposed system. This will enable farmers to take photo of their crop and use the proposed system to detect possible diseases. The given input image is subjected to convolution operation where it computes feature map as in Eq. (1).

$$x_j^{\lambda} = \sum_{i \epsilon M_j} x_i^{\lambda-1} \times k_{ij}^{\lambda} + b_j^{\lambda} \quad (1)$$

The extracted feature map is denoted as x_j^{λ}. The kernel used by the convolutional layer is denoted as kij while λ denotes layers. The input feature map is represented by Mj and bias is denoted by bj. Then the max pooling performs efficient sampling and results in reduction of feature map. The max pooling process is expressed as in Eq. (2).

$$s_j = \max_{i \in R_j} \propto_i \quad (2)$$

In the proposed system, there is need for multiple classes in the classification outcome. For this reason, a softmax utility is used and its proposition is expressed as in Eq. (3).

$$h_{\theta}(x) = \frac{1}{1+\exp(-\theta^{T}x)} \quad (3)$$

ReLU, as activation utility improves learning capability. In other words, it is used to handle over-fitting problem and enable speed in the prediction process. The functionality of activation function is stated in Eq. (4).

$$f(x) = \max(0, x) \quad (4)$$

An algorithm known as Advanced CNN for Plant Disease Detection (ACNN-PDD) is proposed to realize the proposed system.

Algorithm 1: Advanced CNN for Plant Disease Detection (ACNN-PDD).

Algorithm: Advanced CNN for Plant Disease Detection (ACNN-PDD)

Inputs:
D, n, m
(PlantVillage Dataset, number of epochs, batch size)
Outputs:
R, P
(Plant disease detection results, performance statistics)

1. Start
2. Initialize training set vector T1
3. Initialize testing set vector T1
4. (T1, T2)←SplitDataset(D)
5. Create CNN model
6. Add convolutional 2D layers (5 layers are used)
7. Add max pooling 2D layers (5 layers are used)
8. Add fully connected layers (2 layers are used)
9. Add dropout layer (used one layer)
10. F←FeatureSelection(T1)//using conv and pooling layers
11. M = TrainTheModel(F)
12. For each epoch e in n

```
    For each batch b in m
        Update the model M
    End For
End For
M' = FitTheModel(M)
R = Detect(M')
P = PerformanceEvaluation(M')
Print R
Return P
```

D	dataset	n	number of epochs
m	number of batches	T1	training set
T2	test set	R	detection results
P	performance statistics	e	one epoch
b	one batch	M	trained model
F	Optimized feature map	M'	updated model

Algorithm 1 takes PlantVillage Dataset, number of epochs and batch size as input and produce results of disease detection besides performance statistics. The proposed algorithm is evaluated using the procedure as described here. It is based on confusion matrix presented in Fig. 6.

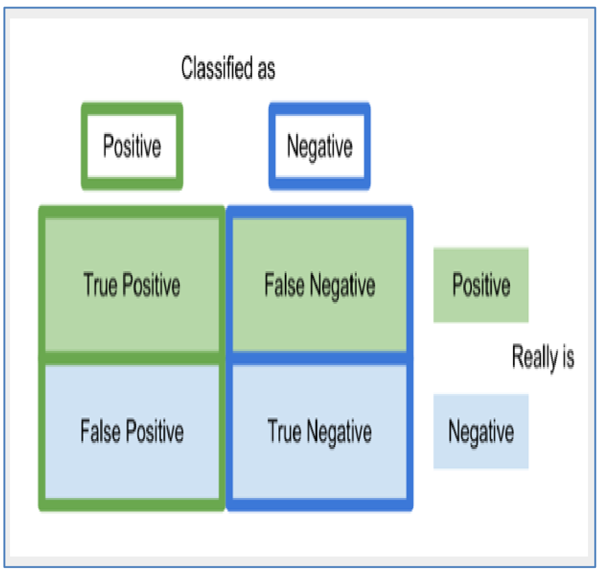

Fig. 6. Illustrates ground truth and predictions through confusion matrix.

Confusion matrix helps in understanding number of correct and incorrect predictions with regard to disease detection. Correct positive prediction is known as True Positive (TP), correct negative prediction is known as True Negative (TN). Opposite to these two (wrong predictions) are known as False Positive (FP) and False Negative (FN) respectively. Accuracy is the metric derived from confusion matrix.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Accuracy is metric used to evaluate performance of the proposed model as expressed in Eq. (5).

V. Experimental Results

Experiments with both PlantVillage dataset [26] and also real time dataset captured from agricultural field are provided here. Then the accuracy of the proposed method is evaluated and compared against prior works.

TABLE I. Hyper Parameters Set in the Proposed Model

Hyper parameter	Value
batch size	128
dropout rate	0.8
learning_rate	1e-3
Loss	categorical_crossentropy
number of epochs	40
Optimizer	adam

As presented in Table I, the hyper parameters used in the proposed CNN model and its values are provided. Batch size indicates that the training process needs to be done in batches. In our research it is set to 128. Dropout rate refers to the fact that contribution of certain neurons is not considered in the learning process. Sometimes, the dropout layer enables the CNN to improve its efficiency by ignoring some inputs. The learning rate is set to control the training process in the proposed system. In our research number of epochs is set to 40 and its does mean the CNN is trained for 40 cycles. Adam is the optimizer used to adjust weights and learning rate in order to minimize loss and improve accuracy in prediction.

A. Results with PlantVillage Dataset

First, we tested the proposed model with test data taken from Plant Village dataset. The results are with two test samples are shown in Fig. 7. The first sample has “yellow leaf curl virus” disease and the proposed system is able to detect it correctly. The second sample also has same disease but with different severity level. The proposed system could detect it also correctly.

<table>
<tr><th>Input</th><th>Output</th></tr>
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Fig. 7. Plant disease detection results using benchmark dataset.

As shown in Fig. 6, the test data is taken from the PlantVillage dataset and the detection results are provided. These results are observed with the test images available in the PlantVillage dataset. Since the dataset has plenty of test samples, the system is initially tested with the readily available samples. Section V(B) presents our empirical study with newly acquired test samples.

B. Results with Real-Time Dataset

We also tested the proposed model with test data captured live from agricultural field. The results are shown in Fig. 8.

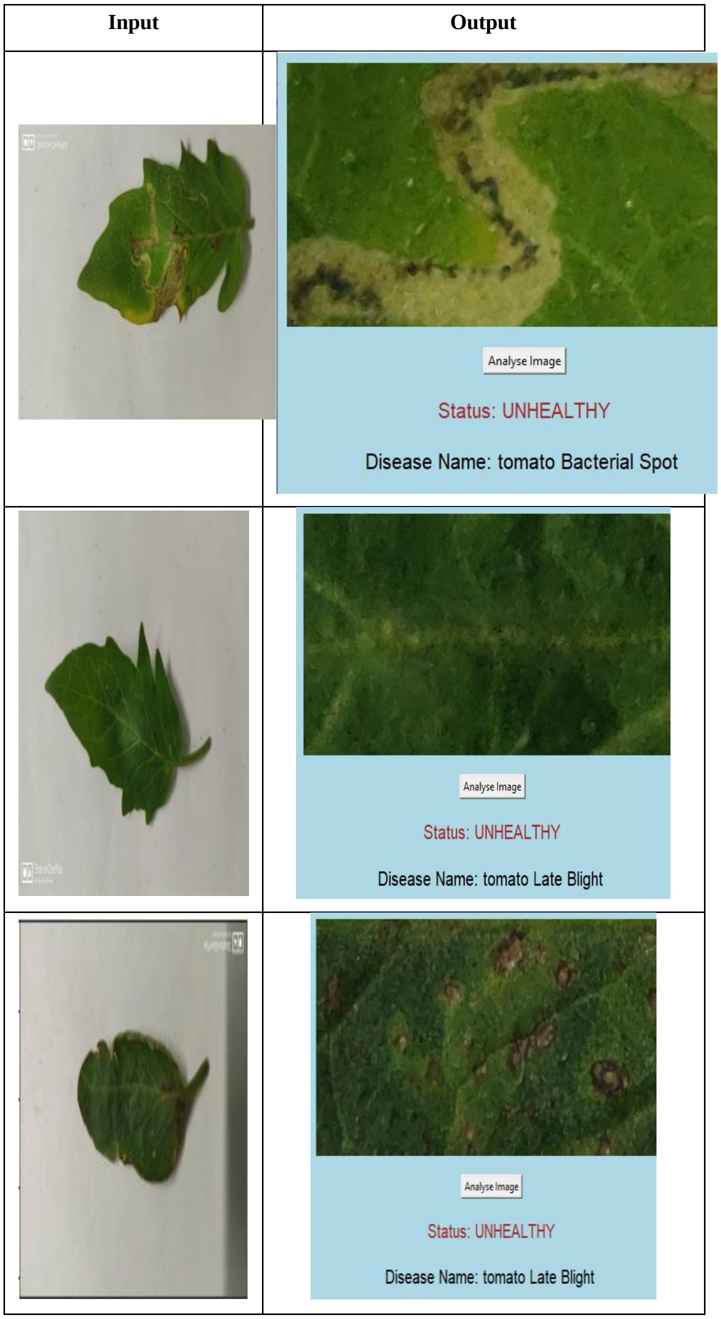

Fig. 8. Plant disease detection results using benchmark dataset.

As shown in Fig. 8, the test data is taken from the real time dataset collected live from agricultural field and the detection results are provided. Since the proposed system works for any crop for whom training data is available in PlantVillage dataset, we did experiments with newly acquired leaves of Tomato crop. Test results for three such samples are provided here. The first sample is detected as "tomato bacterial spot". The second sample is detected as "tomato late blight" while the third one is detected as "tomato late blight". These results are validated and found to be accurate.

C. Performance Evaluation

In this paper compared the detecting performance of our proposed model with many existing deep learning models.

As presented in Table II, the plant disease detection models and their performance in terms of accuracy are provided.

TABLE II. SHOWS PLANT DISEASE DETECTION ACCURACY OF DIFFERENT MODELS

Method	Accuracy
AlexNet	90.46048
GoogLeNet	94.92448
ResNet-20	92.01792
VggNet-16	95.54944
ACNN-PDD (proposed)	96.83904

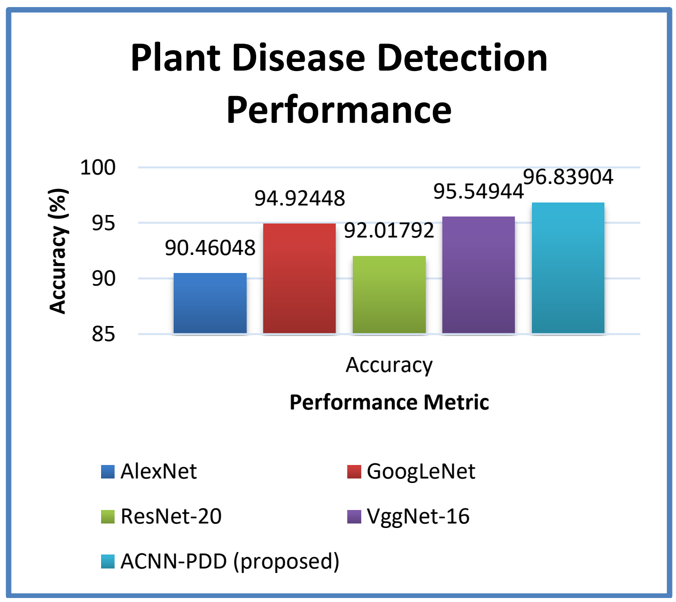

Fig. 9. Performance comparison among plant disease detection models.

As presented in Fig. 9, performance of the models is evaluated in terms of detection accuracy. The detection accuracy is computed by comparing ground truth with predicted values. Different deep learning models showed varied detection performance due to their internal functionality and configuration of layers. Though all the models are based on CNN, their performance is different due to different architecture of the models. Least accuracy is exhibited by AlexNet model with 90.46%. ResNet-20 showed 92.01% accuracy. GoogLeNet has achieved 94.92% accuracy. VGG16 showed 95.54% accuracy. Highest plant disease detection accuracy is exhibited by the proposed ACNN-PDD model with 96.83% accuracy. In summary, our research has resulted in better accuracy as it incorporates layers of the DL model appropriately. Moreover, the model is found robust with both test images from benchmark dataset and also the newly collected samples live from agricultural fields.

VI. Conclusion and Future Work

In this paper, we designed an automatic plant disease detection system by proposing an advanced CNN model. We proposed an algorithm known as Advanced CNN for Plant Disease Detection (ACNN-PDD) to realize the proposed system. Our algorithm has an iterative process that learns from given training samples and ground truth. Then the model is evaluated with test samples. The prediction of ACNN-PDD for each test sample is compared against ground truth to arrive at confusion matrix reflecting efficiency of the model. Our system is evaluated with PlantVillage, a benchmark dataset for crop disease detection result, and real-time dataset (captured from live agricultural fields). The experimental results showed the utility of the proposed system. The proposed advanced CNN based model ACNN-PDD achieves 96.83% accuracy which is higher than many existing models such as AlexNet, GoogLeNet, ResNet-20 and VGG16. Though the proposed model provides better performance, it could be improved further with feature selection enhancements. In future, therefore, we intend to improve our system with further enhancement in CNN model along with feature engineering.

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