# A Deep Learning Framework for Automatic Disease Prediction towards Precision Farming

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**Abstract:- Precision farming is technology-driven agriculture which is meant for improving performance in agricultural activities. With the emergence of Artificial Intelligence (AI), deep learning models are used for solving problems in different domains, particularly in computer vision applications. In this paper, we proposed an intelligent framework known as Deep Learning Framework for Precision Farming (DLF-PF). This framework exploits deep learning approach known as Convolutional Neural Network with enhanced layers for automatic detection of crop diseases. We proposed an algorithm known as Learning based Plant Disease Detection (LbPDD). This algorithm is designed to support CNN based supervised learning for detection of crop diseases. PlantVillege is the dataset used for empirical study in this paper. Our empirical study has revealed that the proposed model showed better performance over existing methods. Our framework is found suitable for usage in agricultural applications towards precision farming.**

***Keywords:-*** *Deep Learning, Agriculture, Smart Farming, Precision Farming, Artificial Intelligence.*

## I. INTRODUCTION

Agriculture plays a vital role in the economic growth of any country. With the increase of population, frequent changes in climatic conditions and limited resources, it becomes a challenging task to fulfil the food requirement of the present population. Precision agriculture also known as smart farming have emerged as an innovative tool to address current challenges in agricultural sustainability. The mechanism that drives this cutting edge technology is machine learning (ML). It gives the machine ability to learn without being explicitly programmed. ML together with IoT (Internet of Things) enabled farm machinery are key components of the next agriculture revolution [2]. Later it was observed that deep learning (DL) models could provide more useful analysis on agricultural data towards precision agriculture [3], [7] and [8]. In most of the recent research articles, supervised learning was given importance due to availability of vast samples in datasets such as PlantVillege dataset [31].

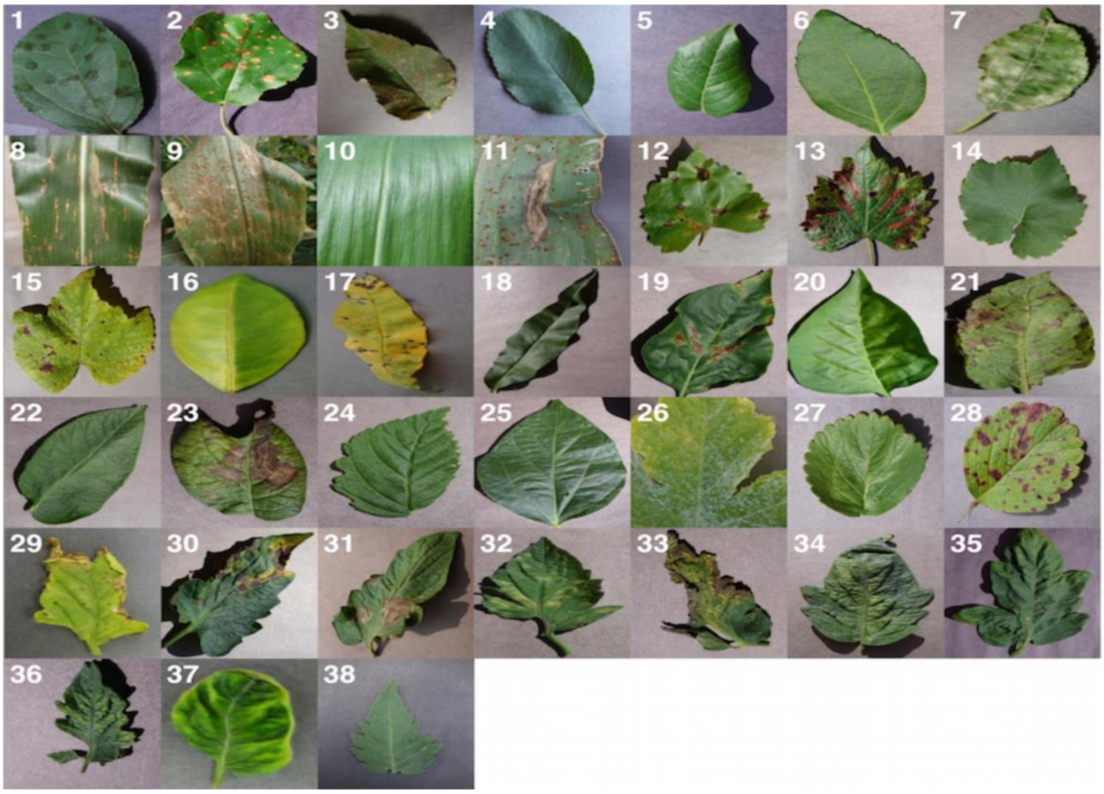


Fig 1 An Excerpt from Plant Villege Dataset [31]

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Figure 1 shows healthy and affected leaf samples across various plants available in PlantVillege dataset. Many researchers found in the literature focused on ML and DL models for crop monitoring in agriculture. In [3] deep learning based methodology was proposed to detect late blight disease in potato along with its severity. It was found in [5] that ML based approaches can lead to sustainable precision agriculture that exploits technology for decision making. In [18] and [19], deep learning models and applications used for smart agriculture are investigated. In [20], the researchers opined that smart farming is made further smarter with the usage of deep learning techniques. Computer vision based phenomena were investigated for the applications in precision agriculture as discussed in [21]. AI based technique is used in [22] for automatic detection of diseases in tomato crop. Deep learning along with transfer learning were explored in [23] for detection of diseases in rice crop. From the literature, it was understood that there is need for leveraging CNN based model for improving accuracy in disease prediction. Our contributions in this paper are as follows.

- We proposed an intelligent framework known as Deep Learning Framework for Precision Farming (DLF-PF).
- We proposed an algorithm known as Learning based Plant Disease Detection (LbPDD) for automatic detection of plant diseases.
- We built an application to know the utility of the proposed framework and underlying algorithm towards plant disease detection.

The remainder of the paper is structured as follows. Section 2 reviews literature on various learning based methods for plant disease detection. Section 3 throws light on the proposed system for technology enabled plant disease detection. Section 4 presents experimental results while Section 5 concludes our work.

## II. RELATED WORK

This section reviews literature on various existing methods based on ML and DL techniques. Precision agriculture initiative has been expressed in many research endeavours. However, the challenges in usage of AI in agriculture along with its utility were studied in [1], [2], [4], [9], [10], [11], [12], [13], [21] and [27]. The essence of these investigations is that ML and DL techniques are used widely in agricultural research that spans crop monitoring to disease detection to identification of crop requirements using IoT technology. In [3] deep learning based methodology was proposed to detect late blight disease in potato along with its severity. It was found in [5] that ML based approaches can lead to sustainable precision agriculture that exploits technology for decision making. ML models were explored in [13], [15], [25] and [28] for automation of crop monitoring, cotton yield estimation, leaf disease detection and food security respectively. Since the agricultural research needs processing of image or video content, many researchers preferred deep learning. In [6], a fusion strategy along with a hybrid architecture using deep learning was used for crop species recognition. In [7] and [8] neural networks and deep learning are used to detect plant stress problems.

In [14] UAV based deep learning and data fusion approaches are used for prediction of Soybean yield. AI enabled approach is used in [16] for making agricultural decisions. IoT technology along with UAV are used in [17 for smart farming practices. In [18] and [19], deep learning models and applications used for smart agriculture are investigated. In [20], the researchers opined that smart farming is made further smarter with the usage of deep learning techniques. Computer vision based phenomena were investigated for the applications in precision agriculture as discussed in [21]. AI based technique is used in [22] for automatic detection of diseases in tomato crop. Deep learning along with transfer learning were explored in [23] for detection of diseases in rice crop. Crop yield prediction and attention based disease detection were incorporated in [25] and [26]. CNN along with autoencoder was used in [29] for disease detection and classification. The usage of deep learning in biomedicine was the main focus in [30]. From the literature, it was understood that there is need for leveraging CNN based model for improving accuracy in disease prediction.

## III. PROPOSED SYSTEM

We proposed an intelligent framework known as Deep Learning Framework for Precision Farming (DLF-PF). This framework exploits deep learning approach known as Convolutional Neural Network with enhanced layers for automatic detection of crop diseases. The proposed framework is based on deep learning. The framework needs training with labelled leaf image samples. Therefore, it is based on supervised learning. It takes care of disease detection and also classification of the disease. Therefore, the framework supports multi-class classification. The proposed framework is based on an enhanced CNN model shown in Figure 2.

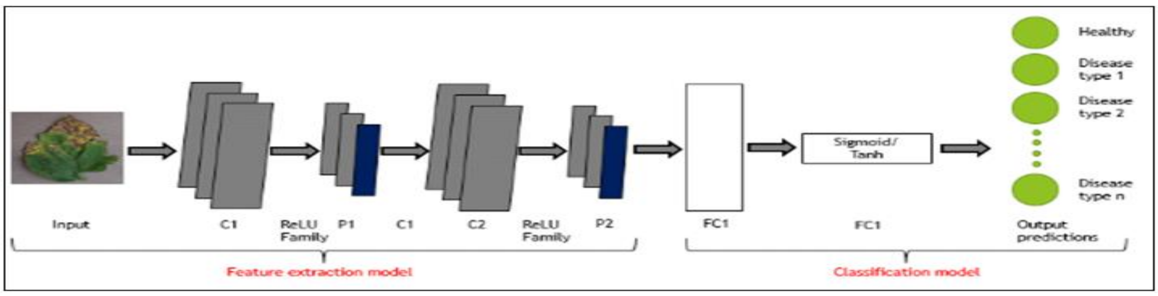



Fig 2 Multi-Class Classification Framework based on CNN Architecture

The framework enables the CNN model to get trained with PlantVillege dataset. This dataset has many kinds of crops and their samples for training. Labelled samples are used for training the CNN model. After the training process, the model is saved for further reuse. In the testing phase, as shown in Figure 2, the deep learning model has different layers configured. The model is divided into two parts. The part 1 is for feature extraction while the part 2 is for classification of diseases. The former is made up of convolutional and max pooling layers. These layers are meant for feature extraction from given input test image and then optimize the features in order to make the classification phase easier and accurate. The classification model has knowledge to discriminate the given image and classify the disease with multi-class classification. We proposed an algorithm known as Learning based Plant Disease Detection (LbPDD). This algorithm is designed to support CNN based supervised learning for detection of crop diseases. PlantVillege is the dataset used for empirical study in this paper.

**Algorithm:** Learning based Plant Disease Detection (LbPDD)
**Input:** PlantVillege dataset D
**Output:** Disease detection results R, performance statistics P

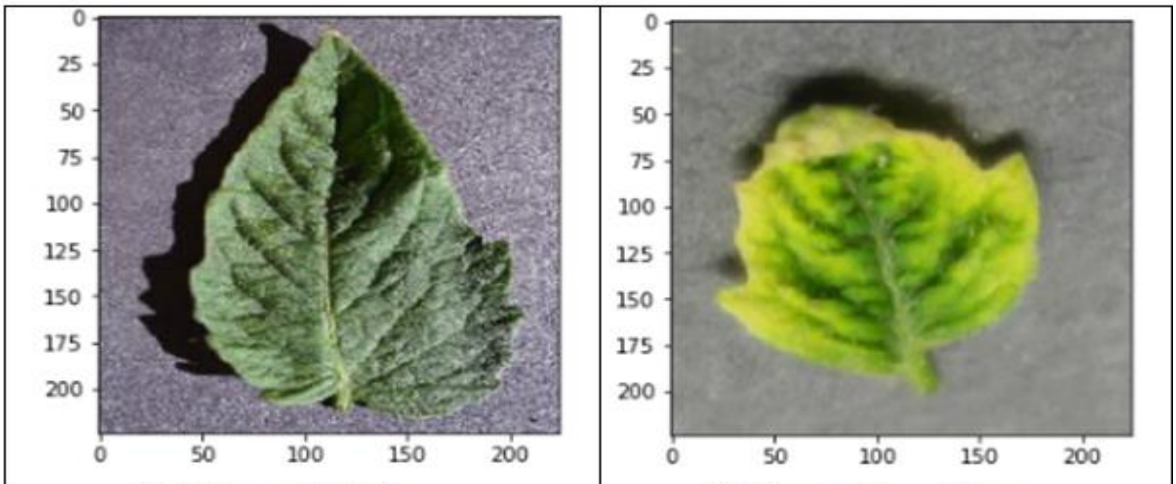
```
Begin
(T1, T2)←PreProcess(D)
model ←CreateCNNModel()
Update model by adding conv layers
Update model by adding pooling layers
Update model by adding FC layers
Compile the model
model←TrainModel(T1)
R←Classify(model, T2)
P←PerformanceEvaluation(R)
Print R
Print P
End
```

Algorithm 1 Learning based Plant Disease Detection (LbPDD)

As presented in Algorithm 1, it takes PlantVillege dataset as input and performs supervised learning process to learning from training data and predict diseases on given test samples. In the process, the algorithm divides dataset into training and test sets. Then the CNN model is created and it is updated with convolutional, pooling and fully connected layers as illustrated in Figure 2. The model is trained with T1 (training data) and the resulted model is used for prediction of diseases using test data T2. The results of predictions and statistics pertaining to performance are final outcomes of the proposed algorithm.

## IV. EXPERIMENTAL RESULTS

We made experiments with a prototype application built. The environment used for developing application is Anaconda, a Python data science platform, where the application is implemented. PlantVillege dataset [31] is used for empirical study. We tested the system with unlabelled samples from the dataset and also live leaf images taken from agricultural crops.




(a) Tomato Healthy (b) Tomato Target Spot

Fig 3 Results of Detection Process

As presented in Figure 3, the proposed system is able to correctly classify given test images. The first image is found to be healthy and the second image is found to be Tomato Target Spot disease.

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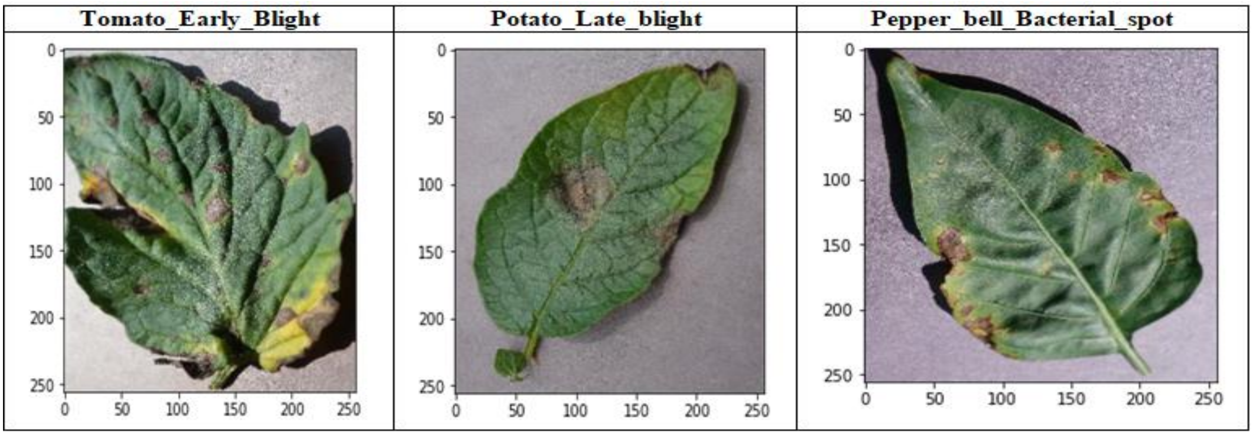


Fig 4 More Results of Disease Prediction Results

As presented in Figure 4, the proposed system is able to detect three different kinds of diseases in three plants such as Tomato, Potato and Pepper Bell.

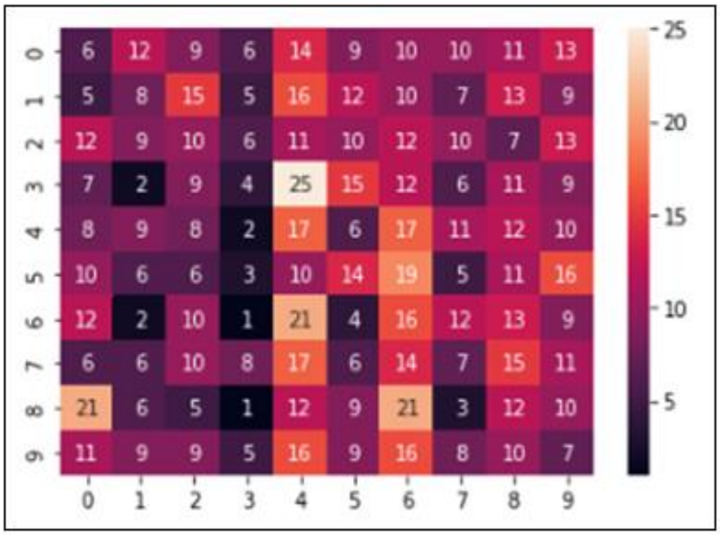


Fig 5 Confusion Matrix for Multi-Class Classification

As presented in Figure 5, the experimental results are provided in terms of confusion matrix for multi-class classification.

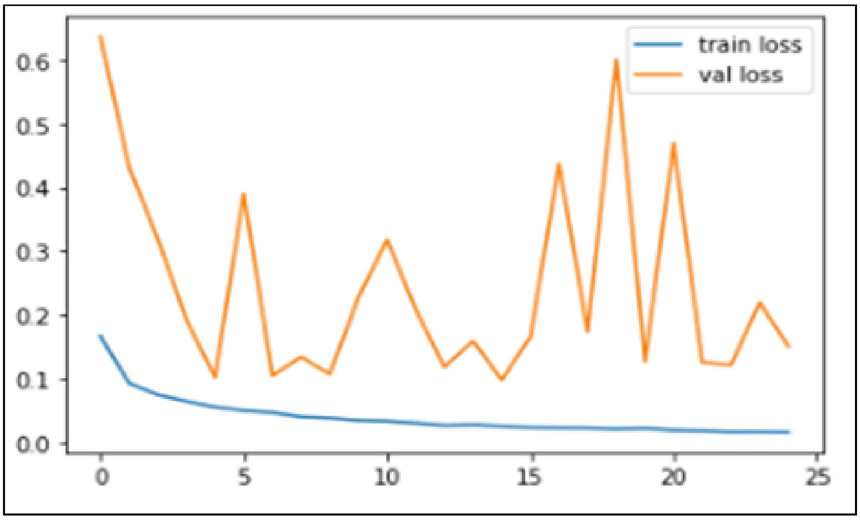


Fig 6 Experimental Results in Terms of Loss

As presented in Figure 6, the experimental results in terms of training loss and validation loss are visualized. Less in loss value indicates better performance. The loss is reduced as the number of epochs is increased.

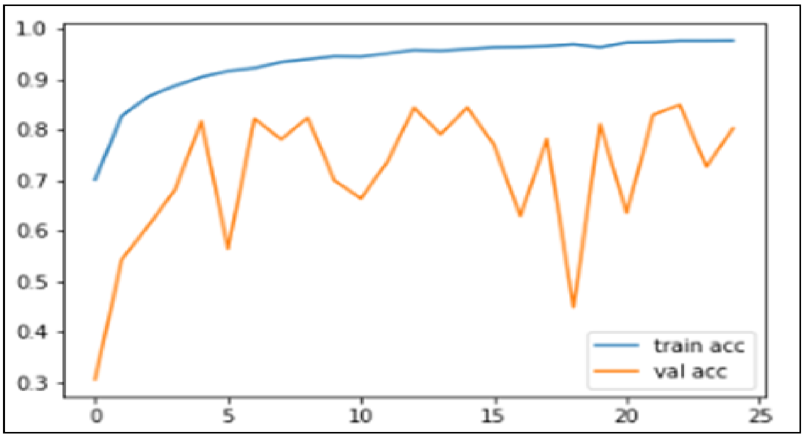


Fig 7 Experimental Results in Terms of Accuracy

As presented in Figure 7, the experimental results in terms of training accuracy and validation accuracy are visualized. Higher in accuracy value indicates better performance. The accuracy is increased as the number of epochs is increased. The proposed model showed highest performance with 96.98% accuracy with 25 epochs.

## V. CONCLUSION AND FUTURE WORK

We proposed an intelligent framework known as Deep Learning Framework for Precision Farming (DLF-PF). This framework exploits deep learning approach known as Convolutional Neural Network with enhanced layers for automatic detection of crop diseases. We proposed an algorithm known as Learning based Plant Disease Detection (LbPDD). This algorithm is designed to support CNN based supervised learning for detection of crop diseases. PlantVillege is the dataset used for empirical study in this paper. Our empirical study has revealed that the proposed model showed better performance over existing methods. The proposed model showed highest performance with 96.98% accuracy. In future, we intend to improve our framework with a hybrid feature selection method along with deep learning for leveraging leaf disease detection process.

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