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Research Article

An Intelligent System for Automated Identification and Categorization of Plant Diseases

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Abstract: Early crop disease detection is an important area of research towards Precision Agriculture (PA). Innovations like Artificial Intelligence (AI) and Internet of Things (IoT) have paved the way for technology-driven agriculture. Towards this end, many researchers contributed in crop disease detection using learning-based methods. However, decease detection accuracy can be further enhanced by improving such models. In the current paper, we propose a deep learning-based crop disease detection framework. We enhanced one of the deep learning models, the Convolutional Neural Network (CNN) to improve its accuracy. We also defined an algorithm named Learning based Crop Disease Detection (LbCDD) which exploits our enhanced CNN for efficient disease detection and classification. It is a multi-class classification model designed to classify all possible diseases. We used PlantVillege dataset for our empirical study. Experimental results showed that LbCDD outperforms many existingmethods. Our framework can be used to be part of a Decision Support System (DSS) in PA applications.

***Keywords*:** agriculture, machine learning, deep learning, CNN, crop disease detection

MSC: 68T05, 62H30, 92-10

1. Introduction

Agriculture across the globe has been witnessing improvements in cultivation and harvesting due to the availability of various machines. However, farmers still suffer substantially due to damage to crops because of unidentified or lately identified diseases. Technological innovations could help governments and organizations to obtain agricultural statistics. However, such technologies could not reach farmers as desired. This is the main problem which has to be addressed to reap benefits of technology-driven agriculture. With the emergence of AI, it is made possible to have intelligent approaches to detect crop diseases and take corrective measures. However, decease detection accuracy can be further improved by enhancing such models.

Iqbal et al. [1] focused on citrus plant diseases using techniques of image processing. They found that image processing is required for plant disease diagnosis. Barbedo et al. [2] explored the principles of deep learning techniques and the significance of applying transfer learning. In the process, they also found the impact of size of dataset and diversity of training samples for accurate classification. Wang et al. [3] used neural network along with attention mechanism besides

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Bayesian optimization for detection of diseases in rice crop. Junde et al. [4] used deep learning equipped with transfer learning. Different image processing techniques are explored in [5] for disease diagnosis. Parul et al. [6] explored various CNN models for plant disease detection. From the literature, there are many insights ascertained. First, most of the researchers preferred CNN model as it could process image data well. Second, CNN models are found to be suitable when tailored based on problem in hand. However, decease detection accuracy can be further improved by enhancing such models.Our contributions are given below.

1. We proposed a learning enabled crop disease detection methodology by enhancing Convolutional Neural Network (CNN).

2. Proposed an algorithm named Learning based Crop Disease Detection (LbCDD) which exploits our enhanced CNN for efficient disease detection and multi-class classification.

3. Evaluation with our prototype revealed that LbCDD outperforms many existing crop disease diagnosis methods.

The remainder of the paper is structured as follows. Section 2 delves into the existing research on utilizing deep learning for the detection of crop diseases. In Section 3, we introduce our framework designed for crop disease detection. Section 4 discloses the outcomes of our empirical investigation. Lastly, in Section 5, we summarize our findings and outline potential avenues for future research.

2. Related work

This portion examines existing literature concerning previous approaches employed in the detection of crop diseases. In [7, 8] there are many deep learning models exploited towards automatic detection of crop diseases. Each model was found to have its architecture and layers designed to solve specific problems. Iqbal et al. [1] focused on citrus plant diseases using techniques of image processing. They found that image processing is required for disease diagnosis. Leaf imagery obtained from fields were used in their study. They could achieve acceptable performance but still their method lacks learning approaches. Nagaraju et al. [9] investigated on various deep learning models used in various empirical studies. Their systematic review has led to valuable insights. Their findings reveal the significant advancements in the learning approaches used in agricultural domain. They also found specific challenges and possibilities with emerging models. Barbedo et al. [10] applied deep learning for detecting plant diseases. In the process, they exploited spots and individual lesions associated with plant leaves. As the leaf images provide symptoms, their method focused on lesions identification. Barbedo et al. [2] explored the principles of deep learning techniques and the significance of applying transfer learning. In the process, they also found the impact of size of dataset and diversity of training samples for accurate classification. Their approach led to reuse of models in more efficient manner. Barbede et al. [11] on the other hand studied the influencing factors on deep learning towards the accurate plant disease detection. The influencing factors linked to their study include the features in learning process and optimization involved in feature engineering besides hyperparameters. Kaur et al. [12] studied leaf image-based techniques in identification of plant diseases. Processing image features could have impact on learning and detection procedures. Wang et al. [3] used neural network along with attention mechanism besides Bayesian optimization for detection of diseases in rice crop. As the models of learning methodology needs to work on given dataset, it became very important to understand the importance of hyperparameter tuning. Abade et al. [13] used CNN models for diagnosis of plant diseases while David et al. [14] explored few-shot learning based on deep learning for disease classification. Their methodologies differ in learning and the latter has provision to improve the learning process. Table 1 shows important findings of the literature.

Table 1. Summary of important literature findings

Reference	Approach	Technique	Algorithm	Data set	Limitation
[7]	Deep Learning (DL)	CNN and Support Vector Machine (SVM)	Back Propagation (BP), Mean Shift, Nesterov Accelerated Gradient (NAG) and Stochastic Gradient Descent (SGD)	Improved Nested Anchor Refinement Single Shot MultiBox Detector (INAR-SSD) and PlantVillege	Early plant disease detection is yet to be explored.
[15]	Machine Learning (ML) and DL	Artificial Neural Network (ANN) and CNN	Deep learning-based algorithm	Custom dataset	To be extended to cover many plant diseases.
[16]	DL	CNN	CNN based algorithm	PlantVillage, iBean, rice and citrus datasets	Missing diversity in plant dataset and model.
[17]	ML and DL	SVM and CNN	Algorithms based on SVM and CNN	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	They intend to improve it with bio-inspired methods and fuzzy logic.
[18]	ML and DL	Deep Neural Network (DNN) and Radial Basis Function (RBF)-SVM	Whale optimization algorithm	Custom dataset	They intend to improve it with diversified datasets.
[19]	DL	CNN and GAN	GAN based algorithm	PlantVillage	In future, then intend to enhance it to classify different parts of a plant.
[20]	ML and DL	Region Proposal Network (RPN), CNN and DNN	Learning based algorithms	PlantVillege	Needs further improvement to support diversified crops.
[21]	ML and DL	SVM and CNN	Jaya optimization algorithm	Dataset created in fields	False positives are yet to be reduced.
[22]	ML and DL	SVM and CNN	Grid search	Rice leaf dataset	They intend to explore other deep architectures in future.
[23]	ML and DL	K-Nearest Neighbors (KNN) and CNN	Otsu algorithm	Potato and Citrus datasets	They intended to improve deep learning models for enhancing accuracy.
[24]	Crop disease detection	Image processing	Convolutional Neural Networks (CNN)	PlantVillage, custom datasets	Requires large labeled datasets for training; sensitive to variations in lighting and background.
	Precision agriculture	IoT and Big Data	Clustering algorithms	Precision agriculture	Data integration challenges; privacy concerns with data collection.
[25]	Irrigation management	Data analytics	Reinforcement learning	Sensor data, weather forecasts	Complexity in modeling dynamic environments; requires real-time data for effectiveness.

Junde et al. [4] used deep learning equipped with transfer learning for disease diagnosis. Similar to the research in [2], they could reuse existing models and expedite learning process for disease diagnosis. Their methodology has thus led to faster convergence. Kamal et al. [26] exploited CNN architectures that are depth-wise separable to detect plant diseases. Such architectures take advantage of using a smaller number of parameters, overcome issues related to overfitting besides making the model computationally in-expensive. Bedi et al. [27] proposed a hybrid model based on CNN and autoencoder to diagnose diseases. Autoencoder based learning techniques have potential to know the abnormalities in the leaf image. Thus, they are good candidates for finding regions affected with diseases. Different image processing techniques are explored in [5] for detection of plant diseases. As discussed earlier, leaf image analysis without a learning phenomenon is conventional in nature. Such methods could be improved with learning-based phenomena. Yang et al. [28] considered

Tomato crop diseases detected using deep learning techniques that focuses on object detection and improvement. Object detection-based methodology has its advantages as input imagery can have number of objects in the image. In fact, such methodology has its merit in quickly identifying intended observations. Tetila et al. [29] investigated pest detection in soybean crop with deep learning using Unmanned Aerial Vehicle (UAV) images. With the advancements in UAV and AI technologies, it became easier to explore automatic agricultural field activities. Parul et al. [6] explored various CNN variants for disease diagnosis. From the literature, there are many insights ascertained. First, most of the researchers preferred CNN model as it could process image data well. Second, CNN models are found to be suitable when tailored based on problem in hand. However, decease detection accuracy can be further improved by enhancing such models.

3. Proposed framework

This section presents complete methodology used in our research including the framework, enhanced CNN model, proposed algorithm and evaluation method.

3.1 *The framework*

We proposed a deep learning framework as shown in Figure 1 for automatic detection of agricultural crop diseases. Deep learning is preferred as it exploits advanced neural networks for solving different kinds of problems. Moreover, learning enabled method for image processing. We used PlantVillege dataset [25] for empirical study. The given dataset is subjected to prior-processing which includes data normalization and data augmentation to improve training quality. The data is divided as 80% training and rest 20% in testing. The training set is given to our enhanced CNN model which learns from data and gains intelligence to be used later for automatic disease diagnosis. The learned model is persisted to secondary storage for further reuse. Then test data is used to perform disease detection.

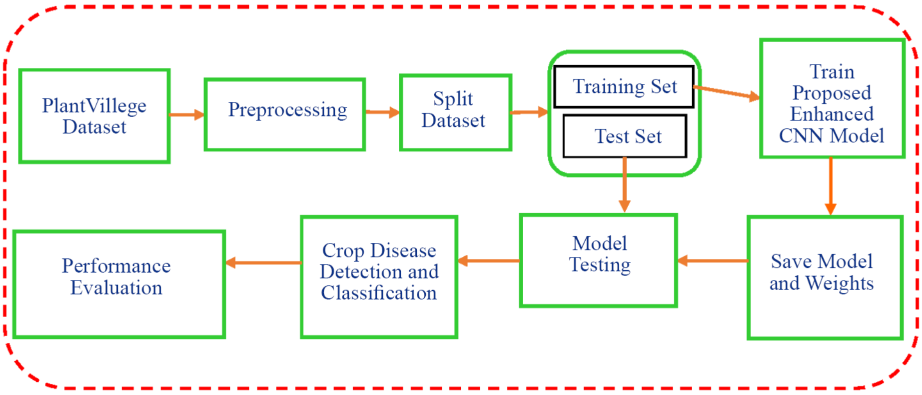


Figure 1. Proposed framework for automatic crop diagnosis

The framework helps in evaluating performance of enhanced CNN model. It is realized with a prototype application which enables users to know whether a crop leaf is healthy or with disease. The framework first detects the presence of absence of disease. Then it has provision to classify the disease. Since it is supervised learning-based approach, quality of training set plays crucial role in the proposed system. CNN model is enhanced with modified configurations to reap its benefits and fit to the problem in hand. Section 3.2 provides more details about our enhanced CNN model.

3.2 *Enhanced CNN model*

The configuration of our improved CNN variant is presented in Figure 2. It has carefully designed layers for processing of leaf images. The convolutional and max-pooling layers are of 2D in nature.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 252, 252, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 84, 84, 32)	0
conv2d_1 (Conv2D)	(None, 82, 82, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 41, 41, 32)	0
conv2d_2 (Conv2D)	(None, 39, 39, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 19, 19, 64)	0
flatten (Flatten)	(None, 23104)	0
dense (Dense)	(None, 512)	11829760
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 128)	65664
dense_2 (Dense)	(None, 15)	1935

Total params: 11,927,535
Trainable params: 11,927,535
Non-trainable params: 0

Figure 2. Layers of the enhanced CNN variant

The CNN model has three convolutional layers and three max pooling layers. The former is used to obtain features from given image while the latter is used to optimize feature maps. Given leaf image to CNN model is subjected to convolution to acquire feature map from the image. The convolution process is expressed in Equation (1).

$$x_j^{\lambda} = \sum_{i\varepsilon M_j} x_i^{\lambda-1} \times k_{ij}^{\lambda} + b_j^{\lambda} \tag{1}$$

The feature map obtained is denoted by x_j^{λ}. The kernel of the layer is denoted by $k_i j$ and the layers is denoted by λ. M_j and b_j denote input feature map and its bias respectively. Efficient sampling process is carried out by max pooling layer which outputs an optimized feature map. The process involved in max pooling is expressed in Equation (2).

$$s_j = \frac{\max \propto_i}{i \in R_j} \tag{2}$$

In the convolutional and dense layers ReLu is the activation function used. This has potential to improve learning process besides handling overfitting issue. It also expedites disease prediction process. This activation function is expressed in Equation (3). Flatten layer in the CNN model is meant for converting data into one dimensional array.

$$f(x) = \max(0, x) \tag{3}$$

In the proposed enhanced CNN model multi-class classification is desired. Towards this end, softmax activation function is employed. This activation function is expressed in Equation (4).

$$\text{softmax}(Z)_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \tag{4}$$

Where raw outputs of neural network are kept in a vector denoted as z while $e \approx 2.718$. For each class i, the softmax function predicts probability to realize multi-class classification.

3.3 *Proposed algorithm*

We defined an algorithm named Learning based Crop Disease Detection (LbCDD) which exploits our enhanced CNN for efficient disease detection and classification. It is a multi-class classification model designed to classify all possible diseases.

As presented in Algorithm 1, it takes PlantVillage dataset as input and performs its mechanisms towards automatic detection and classification of leaf diseases. The algorithm performs preprocessing on the given dataset which improves the quality of samples. Afterwards, the dataset is divided into two parts namely training set with 80% and testing set with 20% of data. They are denoted as $T1$ and $T2$ respectively. The enhanced CNN model is configured, compiled and trained with $T1$. The model is persisted for reusing it as and when required. The model is loaded and used for detection and classification of leaf diseases on the test data. Once the testing phase is completed, the results of classification are evaluated with the help of ground truth to arrive at performance of the proposed deep learning model. The algorithm performs multi class classification on the given test samples.

Algorithm 1 Learning based Crop Disease Detection (LbCDD)
Input: PlatVillage dataset D
Output: Leaf disease classification results R, performance statistics P
begin
    $D' \leftarrow \text{PreProcess}(D)$;
    $(T1, T2) \leftarrow \text{DataSplit}(D')$;
    Configure enhanced CNN model m (as in Figure 2);
    Compile the model m;
    $m \leftarrow \text{TrainTheModel}(T1, m)$;
    Persist model m;
    Load model m;
    $R \leftarrow \text{TestTheModel}(T2, m)$;
    $P \leftarrow$ EvaluateModel(R, ground truth);
    Display R;
    Display P;
end

3.4 *Dataset details*

PlantVillege dataset [25] is used in the experimental study. The dataset has 15 classes reflecting three crops and 15 diseases. Tomato, Potato and Pepper Bell are the three crops considered in the empirical study. The dataset has 16,520 training images and 4,128 test images. Figure 3 shows an excerpt from training set.

Figure 3. An excerpt from training images

Training images are used for supervised learning process to train an algorithm. Then test images are used to evaluate the algorithm. Figure 4 presents some of the test images.

Figure 4. Some of the test images

As the dataset has 15 classes of diseases pertaining to the three crops, the proposed CNN model performs multi-class classification. Table 2 shows each crop and diseases of that crop.

Table 2. Shows the disease classes pertaining to different crops

Crop	Disease classes
Pepper bell	1. Healthy 2. Bacterial spot
Potato	1. Healthy 2. Early blight 3. Late blight
Tomato	1. Healthy 2. Mosaic virus 3. Bacterial sport 4. Early blight 5. Late blight 6. Yellow leaf curl virus 7. Leaf mold 8. Target spot 9. Septoria leaf spot 10. Spider mites

There are 10 classes belonging to Tomato crop while Potato and Pepper Bell crops have 3 and 2 disease classes respectively. Thus a total of 15 disease classes are detected in the proposed crop disease detection system.

3.5 *Evaluation method*

The assessment of the suggested model's performance relies on the accuracy measure derived from the confusion matrix as shown in Figure 5.

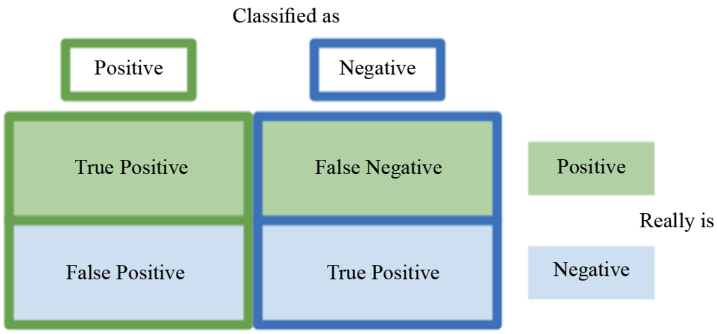


Figure 5. Confusion matrix

True positive indicates algorithm capability to correctly classify given diseased leaf image while true negative indicates algorithm capability to correctly classify given healthy leaf image. False positive refers to an incorrect prediction where given healthy leaf is detected with a disease. Similarly, False negative refers to an incorrect prediction where given diseased leaf is detected as healthy. Equation (5) shows accuracy, a widely used performance metric.

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

Accuracy measure results in a value between 0 and 1. Higher the value indicates better performance.

4. Experimental results

The proposed algorithm LbCDD is evaluated and its results are compared with existing models found in [10, 11, 17]. Plant Village dataset [25] is used for our empirical study. The proposed enhanced CNN model is exploited by the algorithm. It uses 256 $\times$ 256 sized image input. Bath size is set to 32, optimizer is Adam, learning rate is 0.001, loss function is known as categorical cross entropy and number of epochs is set to 15.

The experimental setup is indeed well-structured, with a clear division of the dataset into training and testing sets, which is crucial for assessing the model's. The use of accuracy as the primary performance metric is common and appropriate, especially in classification tasks.

Precision: This metric measures the proportion of true positive predictions among all positive predictions made by the model. Including precision is particularly important in scenarios where the cost of false positives is high. For instance, in a plant disease classification context, misclassifying a healthy plant as diseased could lead to unnecessary treatments.

Recall (Sensitivity): Recall assesses the model's ability to identify all relevant instances, specifically the true positives among all actual positive cases. This metric is crucial when the goal is to minimize false negatives, such as ensuring that all diseased plants are correctly identified to prevent further spread.

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. It is particularly useful in cases of class imbalance, where one class may be more prevalent than others. Including the F1-score would give a more nuanced view of the model's performance, especially in multi-class classification tasks.

Confusion Matrix: Presenting a confusion matrix alongside these metrics would provide a visual representation of the model's performance across different classes. It allows for a quick assessment of where the model is making errors and can guide further improvements.

5. Results

Experiments made with 16,520 training images and 4,128 test images. After completion of training, the model is saved and reused in testing. While testing 4,128 test images are used for evaluating performance. Later on the model is tested with some individual test images. Figure 6 shows an input test image. The Plant Village dataset includes a wide range of crop species and disease types, which provides a diverse set of images representing different plant diseases. However, we ensured that the dataset was balanced in terms of the number of images for each disease category to avoid class imbalance, which could lead to biased predictions. To further address any potential bias and increase the dataset's representativeness, we applied data augmentation techniques, such as rotation, flipping, and scaling. This helped simulate variations in real-world conditions, such as different lighting, angles, and orientations of the crops, which may not have been sufficiently captured in the original dataset.

The given input test image is subjected to different layers of the proposed model. The outcome of the all these layers is the optimized feature map generated as shown in Figure 7.

We were aware of the potential biases in the dataset, particularly in terms of environmental conditions, crop varieties, and disease severity. To mitigate these biases, we used techniques like cross-validation and ensured that the dataset was representative of the target environment. Additionally, we incorporated a pre-processing step to normalize the images and reduce the impact of lighting or camera quality variations.

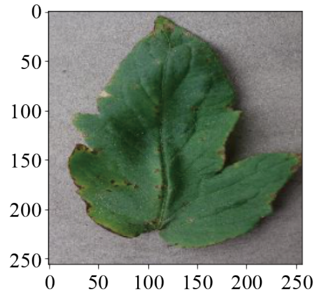


Figure 6. Input image (Tomato leaf with bacterial spot disease)

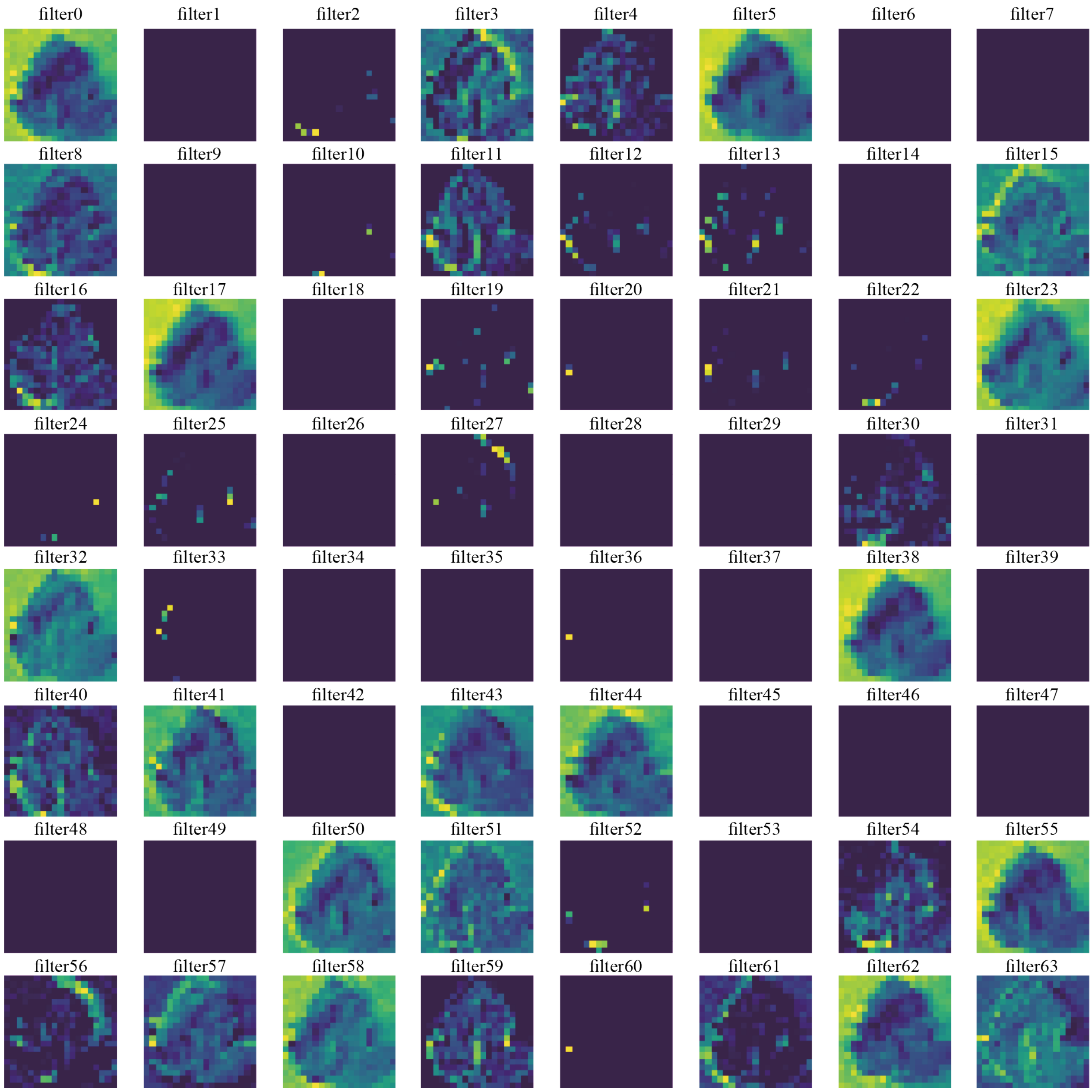


Figure 7. Result after convolutional and max pooling layers

The feature map shows results for 64 filters used in the final max pooling layer. Each filter performs its operations on the acquired features and the resultant values are visualized. Figure 8 shows results of testing individual leaf images.

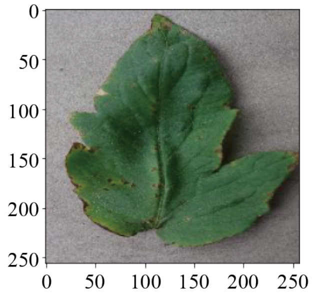
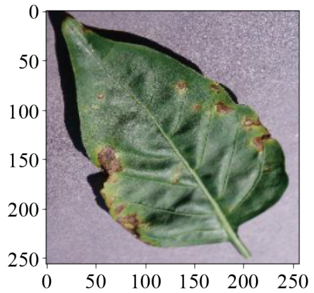
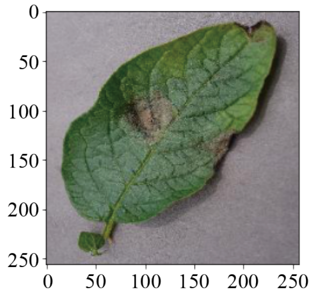
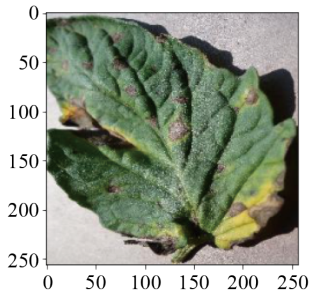
Input image	Identified crop	Ground truth (disease)	Prediction	Correct prediction?
	Tomato	Bacterial spot	Bacterial spot	Yes
	Pepper bell	Bacterial spot	Bacterial spot	Yes
	Potato	Late blight	Late blight	Yes
	Tomato	Early blight	Early blight	Yes

Figure 8. Crop disease detection and classification results

The first input image is detected by the system as Tomato leaf. Then it has processed the image with the knowledge of trained model and detected it as a leaf with disease. Then the system classified the disease as bacterial spot. The second image is detected Pepper Bell leaf with bacterial spot disease. The third input image is correct detected as late blight disease on Potato leaf. The last image is detected as early blight disease on Tomato leaf. Figure 9 presents accuracy details of the model.

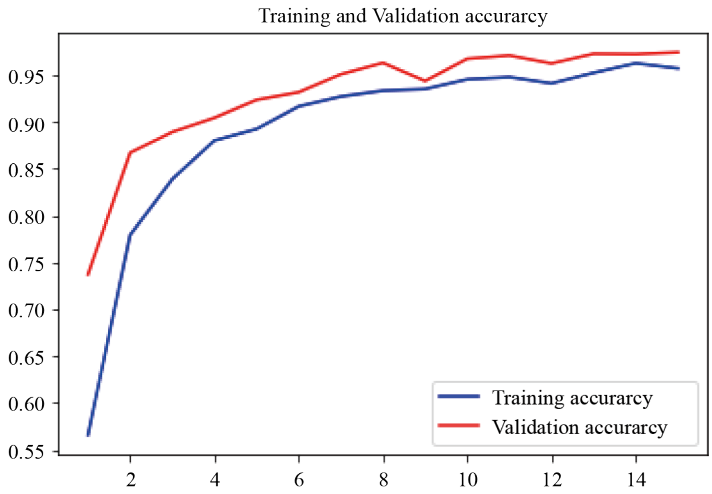


Figure 9. Validation and training accuracy of enhanced CNN model

Vertical axis shows accuracy value while the horizontal axisshows number of epochs. Experiments are made with 15 epochs. As the epochs is increased, the accuracy is gradually increased. At the end of all epochs, the test accuracy achieved by the proposed model is 94.88%. Figure 10 shows validation and training loss of the proposed model.

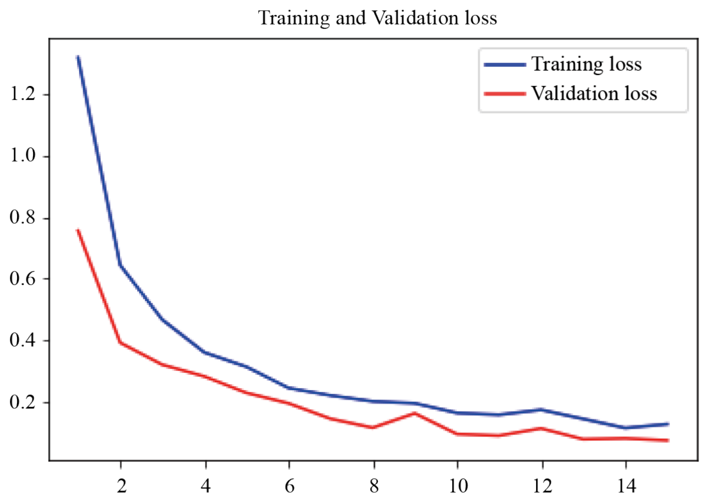


Figure 10. Validation and training loss of enhanced CNN model

Loss against epochs is observed. Experiments are made with 15 epochs. As epochs is increased, the loss value is gradually decreased. Less in loss value indicates better performance. We visualized both the training and validation accuracy and loss curves during the training process. This helped us monitor overfitting or underfitting and adjust hyperparameters accordingly. The curves also provided a clear indication of the model's learning progress and convergence, ensuring that the model was not just memorizing the training data but generalizing well to unseen data.

The choice of Rectified Linear Unit (ReLU) and softmax activation functions is well-justified, as ReLU helps in mitigating the vanishing gradient problem and allows for faster convergence during training, while softmax is appropriate for multi-class classification tasks.

5.1 *Performance comparison*

The proposed LbCDD algorithm with its underlying enhanced CNN model is compared against many existing methods. Table 3 presents performance comparison among different models including the proposed one.

Table 3. Shows performance comparison

Disease detection model	Accuracy (%)
Barbedo [10]	91.29
Sujatha et al. [17]	89.5
Jayme [11]	87
Proposed (LbCDD)	94.88

Each model is found to have different level of accuracy due to its modus operandi in learning process and detection of crop disease. Figure 11 visualises the performance of different models.

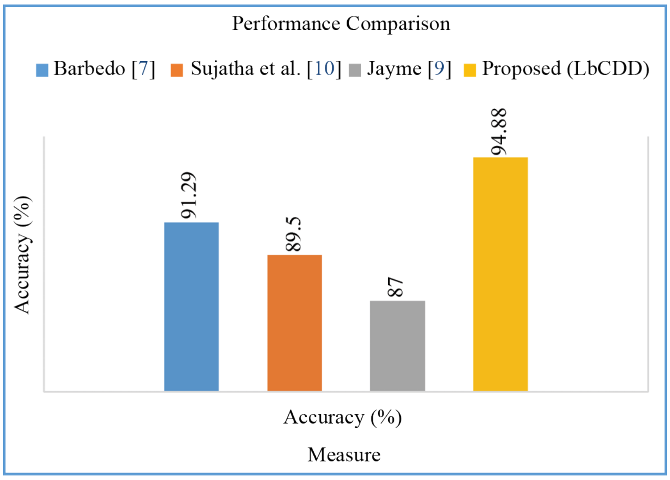


Figure 11. Accuracy of models used for crop disease detection

Accuracy refers to correctness in detecting plant diseases. The proposed system is evaluated for its accuracy in plant disease detection. Then its performance is compared against existing models discussed in [10, 11, 17]. Least accuracy is exhibited by the model proposed by Jayme [11] with 87% accuracy. The model proposed by Sujatha et al. [17] showed better performance over [11] with 89.50% accuracy. The deep learning model proposed by Barbede [10] performed better than that of [11, 17]. The proposed model used in the algorithm LbCDD exhibits highest accuracy among all models with 94.88%. The proposed system has limitations as well. First, it can detect only diseases of three crops. However, it is capable of working for any crop and any disease provided training with such crops. Second, the training samples is only 16,520 and this number could be increased for further enhancing accuracy of the model.

6. Summary and prospects for future research

A framework/structure is proposed for efficient crop disease diagnosis. The given dataset is subjected to pre-processing, data normalization and data augmentation to improve training quality. The dataset is used in 80% and 20%

ratio for training and testing. The training set is given to our enhanced CNN model which learns from data and gains intelligence to be used later for automatic plant disease detection. We enhanced CNN for improving its accuracy. We also proposed an algorithm known as Learning based Crop Disease Detection (LbCDD) which exploits our enhanced CNN for efficient disease detection and classification. It is a multi-class classification model designed to classify all possible diseases. We used Plant Village dataset for our experimental study. Experimental results showed that LbCDD outperforms existing methods. Our algorithm showed highest accuracy with 94.88%. Our framework can be improved in future with Region of Interest (ROI) along with deep learning models for leveraging detection accuracy further.

Conflict of interest

The authors declare no competing financial interest.

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