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Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images

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ABSTRACT

Plant diseases are one of the major concern in the agricultural domain and their automatic identification is very crucial in monitoring the plants. Most of the disease symptoms are reflected in the leaves of plants but the leaf diagnosis by experts in laboratories are costly and time-consuming. In this paper, a deep-learning-based approach is presented for the plant disease detection and classification from leave images captured in various resolutions. Dense convolutional neural network architecture is trained on a large plant leaves image dataset from multiple countries. Six crops in 27 different categories are considered in the proposed work in laboratory and on-field conditions. Images have several inter-class and intra-class variations with complex and challenging conditions that have been addressed in this dense neural network. Five-fold cross-validation and testing on unseen data is done for exhaustive evaluation of the trained model in various parameters. Experimental results proved that the proposed deep learning-based system can efficiently classify various types of plant leaves with good accuracy. The experimental findings demonstrate that an average cross-validation accuracy of 99.58% and average test accuracy of 99.199% is obtained on unseen images with complex background conditions. The processing time to process a single plant leaf image is 0.016 s with significant accuracy which signifies its real-time performance.

1. Introduction

Plant diseases are one of the significant causes of the loss of crops. They can affect the quality of crops and dwindle their production. It can lead to famines and a rise in unemployment in the agriculture sector. Agriculture is one of the primary occupations in developing countries like India. The loss of crops can severely affect the economy of the country. The lack of awareness among the farmers is a significant challenge for detecting plant diseases and taking appropriate actions to prevent the loss of crops. Crops are influenced by a wide variety of infections particularly in temperate, tropical, subtropical parts of the world. Then, plant infections are due to some viruses, fungi, bacteria, moulds or sometimes may be due to the environmental factors, for example, precipitation, temperature, and humidity that subsequently act as a vector for infection from viruses, plagues and other pathogens. These infections can cause substantial financial loss and impact the livelihood of farmers. The quantity and quality of the crop in the development of agriculture can be enhanced if plant disease can be successfully dealt (Yang and Guo, 2017). Plant diseases cause massive damage to crops and a shortage of food which is a challenge for sustainability and food security of people. Thus, early detection of plant diseases become essential to control and manage the crops. Human expertise is usually used to diagnose the plant diseases but availability is inconsistent and scarce in remote locations and villages in developing countries. In addition to that, traditional methods which were used by the farmers and field experts for detecting the plant infections are quite expensive, time consuming, and are prone to errors. Hence, artificial intelligence based methods can play a vital role in fast and more accurate plant disease detection methods.

Latest image processing and pattern recognition techniques have discovered some solution towards disease recognition to help farmers and agriculture experts. The quality of agriculture and aquaculture products can also be estimated based on the images and applying different artificial intelligence based techniques in an automatic manner (Singh et al., 2017). Images of the different part of the plants can be captured to develop a plant disease detection system. Plant leaves are considered as the most common part to detect plant diseases. Even image processing techniques are efficient to detect the plant diseases but

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these techniques are susceptible to disparities in images of leaves due to shape, colour, texture, image noise, etc. These images can be employed to train machine learning and deep learning models. In recent years, different concepts of deep learning can be used in the domain of agriculture to deal with different issues like pest detection, fruit detection, plant leave classification, fruit disease detection, and leaf disease detection. Disease detection with traditional machine learning methods is very difficult for real-time implementation. Thus, deep learning methods can help in direction to deal with these difficulties to develop expert systems in the advancement of the agriculture sector. Different approaches have been used for the detection and identification of plant diseases. Image analysis of plant leaves is highly complex where most of the symptoms related to the different disease can be seen. Due to this complex nature of the phytopathological problems and large variety of crops, even agronomist experts find problem to diagnose plant diseases. Thus, deep learning and computer vision assisted systems can provide better assistance to the field experts and farmers in the diagnosis of plant diseases from the analysis of input leaf image.

With the advent of smartphones and the development of mobile applications, simple and easy to use applications can be build up to provide better agricultural infrastructure and advice related to the plant disease diagnosis. New prototypes can be developed which can be utilized with the autonomous agricultural vehicles which can do monitoring of the plants and crops for rapid and timely detection of phytopathological issues from a live image acquisition device. These devices can be controlled and monitored with mobile or computer application with custom area selection in an easy-to-use framework. One such initial framework was developed which utilises the image processing techniques with some statistical parameters to tackle the plant disease detection problem (Johannes et al., 2017). Candidate hot-spot detection is done using mobile devices for the wheat crop.

Advancement in the field of Graphical Processing Units (GPU) based processors and research on new machine learning and artificial intelligence-based applications lead to the development of the field of deep learning which is an advanced filed of machine learning. Deep learning architectures mostly composed of a large number of layers which is much different to traditional neural networks. Researchers have employed various machine learning and deep learning techniques for plant disease detection. Basic machine learning methods used the user-defined features and these features are used to differentiate images in different categories. But deep learning methods determine the features on its own from the various layers of the architecture for this purpose of detection and classification.

Support vector machine (SVM) has been utilized for long to recognise various plant diseases such as grape leaf diseases (Padol and Yadav, 2016), potato blight diseases (Patil et al., 2017), palm oil leaf diseases (Masazhar and Kamal, 2017), etc. SVM is the supervised learning technique for data classification using associated learning algorithms but need handcrafted features to make proper differentiation in different classes (Singh et al., 2017). Artificial neural network (ANN) classifiers with SVM are trained for extraction of texture and colour features from plant leave images which achieved an accuracy of 92.17% on test set images (Pujari et al., 2016). An image processing based improved KNN algorithm with the k-means method in Lab colour space is used for the classification of rice blast which is one of the critical problem (Larijani et al., 2019). The overall accuracy of 94% was achieved with this method to detect the rice blast. Chlorosis is a plant disease and also known as yellowing disease which is prevalent in plants of black gram. A computer vision-based method for Chlorosis identification was proposed using a support vector machine and obtained an accuracy of 95.69% on plant leaf images (Pandey et al., 2021).

As machine learning and other statistical methods need manual features for its operation, it suffers lack of performance. Thus, deep learning-based methods came into the existence to diagnose different plant disease in large databases. A convolutional neural network was proposed for classifying the leaves of *Vigna mungo* plant into healthy, mild and severe categories (Joshi et al., 2021). The images are trained on the sequential network with different pre-processing techniques. The model achieved a test accuracy of 97.403% on images of different categories. In another deep learning-based approach, EfficientNet architecture (Tan and Le, 2019) is used for the task of plant leaf disease classification and laboratory images of different varieties were used to train the model using transfer learning (Atila et al., 2021). Hyperspectral imaging is also used for identification of plant species in alpine steppes of Northern Tibet under field conditions. In tedious conditions of high spatial homogeneity, principal component, spectral indices, continuum removal, and derivatives were used for making well differentiation between plant species (Liu et al., 2021). Four different machine learning-

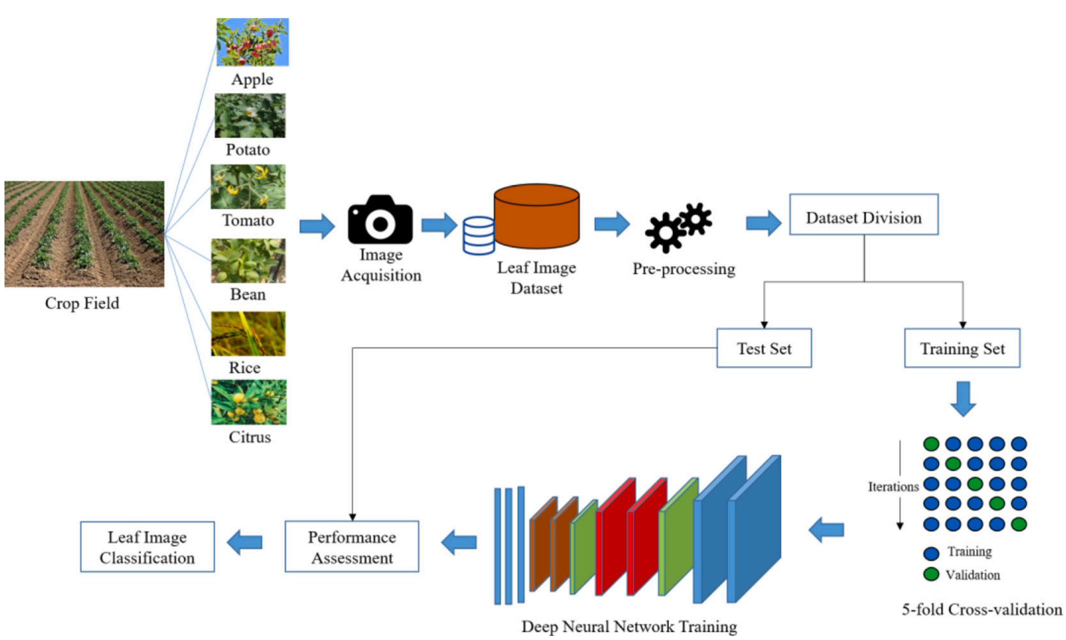


Fig. 1. Block diagram of the proposed plant disease detection and classification framework.

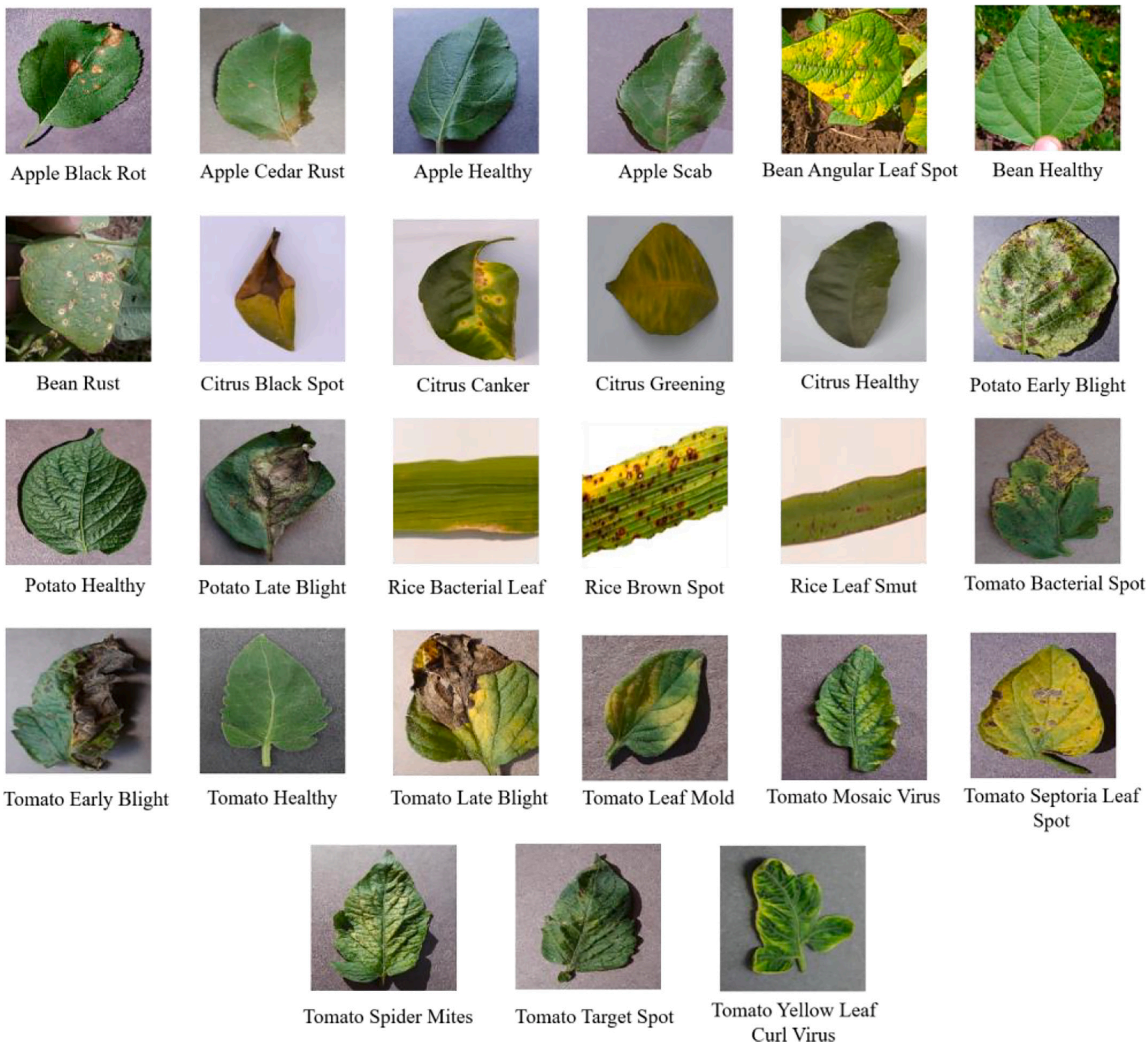


Fig. 2. Sample leaf images of 27 different categories used in the proposed work.

based approaches were used and yielded the highest accuracy of 94.73%. Imaging and convolutional neural network method was employed for bacteriosis which is the common disease in peach crops (Yadav et al., 2021). Various adaptive operations for selection of suitable channel of the colour image and grey-level slicing for pre-processing leaf images. The overall accuracy of 98.75% is obtained for bacteriosis detection with deep learning model. A computer-assisted network named PD2 SE-Net was developed to detect different plant diseases and their estimation of severity (Liang et al., 2019). Five crops were taken for study in three different categories and Resnet-50 architecture is taken as the base network for training different images. In another work, a method employing transfer learning is proposed for disease detection in Casava plant and achieved an accuracy of 93% in unseen images (Ramcharan et al., 2017). All the existing research and reported outcomes are motivating, but still, there is a need to explore the more possibility to develop artificial intelligence-based systems using advanced neural network architectures with significant accuracy in the domain of plant species recognition with disease detection and classification. Such automated classification frameworks should be trained with multiple number of crops in different classes and imaging conditions to enhance their robustness and efficiency.

The main contribution of the proposed work is to develop a deep-learning based plant disease detection and classification system. Plant leaves images of six crops in 27 different categories has been considered based on their health and disease category. The collected dataset uses images from databases of multiple countries for global wide acceptance of proposed framework. The images consist of both laboratory and on-field images to develop a robust framework. A large dataset of collected images in various categories is used to train dense convolutional neural network architectures for multiple iterations. Images have significant inter-class and intra-class variations with complex background conditions. Collected dataset is divided into training, validation and testing set for training and examining the framework. 5-fold cross-validation and testing on unseen images are done for proper

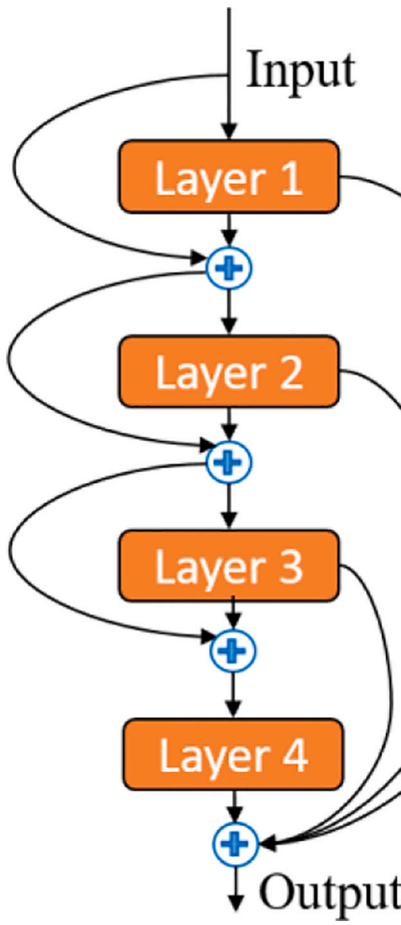


Fig. 3. Dense Block with four layers.

evaluation of the accuracy and efficiency of the trained architecture. The proposed deep learning-based method outperforms other methods and has achieved an accuracy of 99.58% on 5-fold cross-validation and 98.199% accuracy on other unseen test images. The proposed framework shown results with good efficacy which works in real-time, resolution invariant and can be integrated with camera-based systems for monitoring of plant health and timely detection of diseases.

The rest of the paper is structured as follows. Section 2 elaborates on the data collection and the deep neural network architecture. Experimental results have been discussed in Section 3. Section 4 concludes the proposed work.

2. Materials and methods

To develop a framework for plant disease detection and classification system multiple steps has to be taken from data collection, model training and multiple-class classification of plant leaves. The proposed framework is summarized using the block-diagram as shown in Fig. 1. Different leaves of the plant belonging to six different crops are collected in 27 different categories. The images in the proposed work are collected from different datasets having different resolutions which were converted into the same dimensions according to input layer of the deep learning architecture. After developing a proper dataset, the collected dataset is divided into training, validation and testing set. Then, a deep learning architecture is trained for the multiple numbers of epochs using that data. The performance of the trained model is evaluated on various

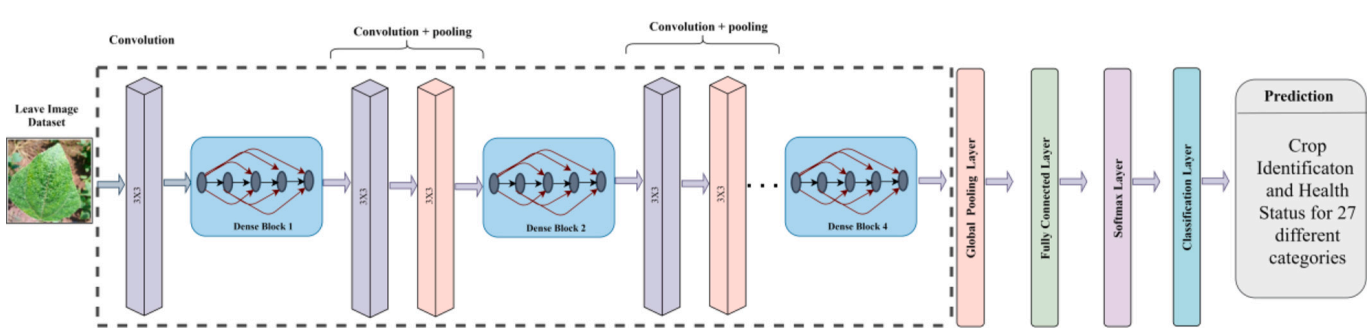


Fig. 4. Proposed plant disease classification framework using DenseNet-201 architecture.

Layers	Output Size	Architecture
Convolution	112×112	7×7 Convolution, Stride 2
Pooling	56×56	3×3 max pool, Stride 2
Dense Block 1	56×56	$\begin{bmatrix} 1 \times 1 \text{ Convolution} \\ 3 \times 3 \text{ Convolution} \end{bmatrix} \times 6$
Transition Layer 1	56×56	1×1 Convolution
	28×28	2×2 Average pool, Stride 2
Dense Block 2	28×28	$\begin{bmatrix} 1 \times 1 \text{ Convolution} \\ 3 \times 3 \text{ Convolution} \end{bmatrix} \times 12$
Transition Layer 2	28×28	1×1 Convolution
	14×14	2×2 Average pool, Stride 2
Dense Block 3	14×14	$\begin{bmatrix} 1 \times 1 \text{ Convolution} \\ 3 \times 3 \text{ Convolution} \end{bmatrix} \times 48$
Transition Layer 3	14×14	1×1 Convolution
	7×7	2×2 Average pool, Stride 2
Dense Block4	7×7	$\begin{bmatrix} 1 \times 1 \text{ Convolution} \\ 3 \times 3 \text{ Convolution} \end{bmatrix} \times 32$
Classification Layer	1×1	2×2 Global Average pool
		27 D Fully connected, Softmax

Fig. 5. Architectural details of the deep learning network.

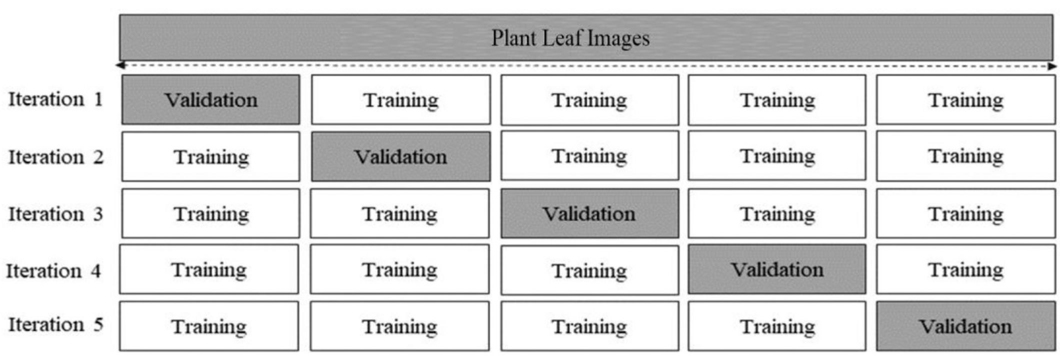


Fig. 6. Representation of 5-fold cross validation method.

parameters. The trained model after 5-fold cross-validation also tested on the unseen images belonging to all categories.

2.1. Leaf dataset collection

To develop a proper leaf classification and disease identification algorithm, models are trained and evaluated on a certain dataset. Different images belonging to the various diseased and healthy class of plants are collected from the four different datasets. First one is the PlantVillage dataset (Mohanty et al., 2016) from where 26,590 images leaf classes were taken. These leaf images belong to three crops i.e. Apple, Potato, and Tomato. It has 17 different classes (4 classes of Apple, 3 classes of Potato and 10 classes of Tomato). Out of 17, three classes belong to the healthy category for each crop and the rest of the leaf images belonged to the disease category.

The second dataset is the latest iBean leaf image dataset (AIR Lab Makerere University, 2020) which is collected by the Makerere AI lab from the field from various districts in Uganda in association with the National Crops Resources Research Institute, the national body responsible for regulating agricultural research in Uganda. Beans are cultivated by many small-scale farmers in Africa and is a major cereal crop. It is a principal source of protein for children. These images belong to three different classes; one is healthy and the other two are diseased leaf categories, i.e. Angular Leaf Spot and Bean Rust. The images are open field images which will help to develop a robust model to work on both lab conditions and on-field conditions. Total 1296 leaf images are collected in three different categories with more than 425 images in each category.

The third dataset is of the citrus leaf images (Rauf et al., 2019) which have five different classes, i.e. Blackspot, Canker, Scab, Greening, and Melanose. A total of 609 images were there in the dataset. A total of 609 leaf images were in this dataset and out of these 5 classes only four classes has been considered in the proposed work as the Melanose category has only 13 images which are quite insufficient to divide the

Table 1
Different images in different classes of plant leave images.

S. N.	Class	Total Images	Train	Validation	Test
1	Apple Black Rot	621	448	111	62
2	Apple Cedar Rust	275	199	49	27
3	Apple healthy	1645	1185	296	164
4	Apple Scab	630	454	113	63
5	Bean angular leaf spot	432	312	77	43
6	Bean Healthy	427	308	76	43
7	Bean Rust	436	314	78	44
8	Citrus Black Spot	171	124	30	17
9	Citrus Canker	163	118	29	16
10	Citrus Greening	204	148	36	20
11	Citrus Healthy	58	42	10	6
12	Potato Early Blight	1000	720	180	100
13	Potato healthy	152	110	27	15
14	Potato Late Blight	1000	720	180	100
15	Rice Bacterial Leaf Blight	40	29	7	4
16	Rice Brown Spot	40	29	7	4
17	Rice Leaf Smut	40	29	7	4
18	Tomato Bacterial Spot	2127	1532	382	213
19	Tomato Early Blight	1000	720	180	100
20	Tomato healthy	1591	1146	286	159
21	Tomato Late Blight	1908	1374	343	191
22	Tomato Leaf Mold	952	686	171	95
23	Tomato Mosaic Virus	373	269	67	37
24	Tomato Septoria Leaf Spot	1771	1276	318	177
25	Tomato Target Spot	1404	1012	252	140
26	Tomato Two Spotted Spider Mite	1676	1207	301	168
27	Tomato Yellow Leaf Curl Virus	5357	3857	964	536
Total		25,493	18,368	4577	2548

dataset and its proper evaluation. Citrus is a significant source of nutrients like vitamin C. Citrus diseases adversely affect the quality and production of Citrus fruits. The images were captured from the Sargodha region, a tropical area in Pakistan and have a size of 256*256 pixels with 72dpi resolution.

The fourth dataset is of rice leaf images (Prajapati et al., 2017) having three different disease categories i.e. Bacterial leaf blight, Brown spot, and Leaf smut. It consists of 120 images categorized into three classes on the basis of the type of disease. Each class consists of 40 images. The pictures were clicked in direct sunlight with a white background. The resolution of the images was reduced to the desired value for processing. Images were segregated manually into different classes. The leaves were collected from a rice field from Shertha, a village in Gujrat, India. The farmers labelled the leaves using the names in the native language. The experts were consulted to determine their English names. The images have uneven illumination intensities and complex background conditions. Deep learning models were trained and evaluated on images of plant leaves for classifying and identifying disease on images that the model has not seen before. Sample images belonging to different categories of the plants and their diseases are shown in Fig.2.

2.2. Dense convolutional neural networks

Deep learning has revolutionised the field of image classification and computer vision. The general architecture of deep convolutional neural network composed of multiple numbers of layers e.g. convolutional layer, pooling layers, fully connected layers with other activation functions. The input data is moulded into the dimensions of the input layer of the convolutional neural network. Then the input data passes through the multiple layers and features are extracted layer by layer to learn the object class and to differentiate well from the other classes.

Dense Convolutional neural network, DenseNet is collaboratively developed by Facebook AI research, Cornwell University, and Tsinghua University (Huang et al., 2017). The philosophy behind using the dense convolutional neural networks is that if deep neural networks contain shorter connections between layers close to the input and those close to the output, it can be substantially efficient, more accurate, and deeper to train the network. In convolutional neural network, each layer is connected to every other layer in a feed-forward manner. Traditional convolutional neural networks with n number of layers have n number of connections, one between each layer and its successive layer. But there are $n(n + 1)/2$ direct connections in case of dense convolutional. The feature maps of all previous layers are taken as inputs in each layer and feature maps of its own are used as inputs into all successive layers. Dense Block with four layers is shown in Fig. 3 in which input is given to first layer to generate k numbers of feature maps and these are concatenated with the input. Similarly, second layer is applied to generate another k number of feature maps and these are concatenated with the preceding layer. Thus, for 'N' layered dense block generate N*k number of feature maps.

Dense connectivity has enhanced the accuracy of neural network architecture with few numbers of parameters as compared to other models with a large number of parameters such as ResNet, AlexNet etc. As there is no need to relearn redundant feature maps in dense connectivity pattern, it requires fewer parameters than traditional convolutional neural networks. DenseNet201 has multiple numbers of layers and has shown high performance. The word 'dense' in DenseNet signifies that every layer has a connection with all preceding layers. Feature reuse and gradient flow is another advantage of these kinds of architectures. The DenseNet201 becomes easy to train by exploiting the condensed network. The input of the subsequent layers has significant variation due to feature reuse functionality used by different layers to increase the performance.

In the ImageNet (Krizhevsky et al., 2017) and CIFAR-100 database (Krizhevsky et al., 2009), DenseNet also achieved a state-ot-art performance with a fewer number of parameters in comparison to other deep learning architectures. More information can be extracted from the input images in dense networks. The input image size of plant leaves to the training deep learning dense model is 224 X 224 pixels. In DenseNet architecture, 16 output channels used to convolve an input image which is given to the dense blocks. All layers are directly connected in a feed-forward manner with each other layer in each dense block. The DenseNet201 model for plant disease detection and classification task is shown in Fig. 4. All the feature maps at each layer gathered from preceding layers are separately considered and given as input after concatenating in a form of single tensor. Rectifier Linear Unit (ReLU) is chosen as an activation function due to its computational efficiency as compared to the other activation functions.

The architectural detail of all the layers with output size is given in Fig. 5 which has 201 layers (1 convolution, 1 classification, 3 transitions, $((6 + 12 + 48 + 32)*2 = 196)$ layers in dense blocks). Convolutions of 3×3 and batch normalisation are also done after applying previously generated feature maps. A transition layer is placed in between the dense blocks which are composed of 1×1 convolution and 2×2 average pooling layer after applying the batch normalisation

The final dense block is connected to a global average pooling layer which is succeeded by the connecting a softmax classifier at the end. Then classification is done for all the trained labels and the similar procedure is followed while testing a plant leave image. The input plant leaf image is resized into the dimension of 224×224 pixels and processed in different convolutional layers and dense block. After a block by block processing trained model predicts the images in the category which has most matched extracted features. Dropout strategy is used by the first two layers of the fully connected layers which randomly blocks certain neurons on the basis of a specified probability value to prevent the occurrence of overfitting in deep learning architectures. The diseases cause change in the leaf due to infection and form different patterns on them which can become a visual features for a deep learning algorithm. The deep learning model tries to learn different patterns formed due to disease and shape of the leaf images to distinguish from other category of infected and heathy images.

3. Experiment and results

The deep learning-based plant disease detection and classification framework is trained with various leaves images different crops in the device having Intel Xenon processor with 64-bit Windows 10 operating system, 64 GB RAM, NVIDIA Quadro P600 GPU with 24 GB memory. Programming framework is Python using Tensorflow, Keras, PyTorch, and OpenCV libraries in Anaconda Jupyter Notebook. The batch size was taken as 32 and the input size of the images were 256 X 256 pixels. Stochastic Gradient Descent (SGD) is used as optimizer due to its high performance over Adam optimizer. Learning rate of 0.001 is taken in this work. The value of momentum is taken as 0.9 and 100 number of epochs were taken as 100 as performance get almost saturated after 60 epochs.

The collected dataset is divided into three sets, training set, validation set and test set. Test set is composed of randomly selected 10% of total collected images and kept apart as unseen images. After separating 10% plant images from each category, remaining images were split into training and validation sets. Five-fold cross-validation was done to make a proper evaluation of the trained model. The main advantage of cross validation is to make use of all data points in the dataset and which results into low bias. To perform 5-fold cross-validation, data is divided into five parts and four parts are used as the training set whereas one part is used as a validation set. The validation set for five iterations is taken such as there is no overlapping of the images. The process of 5-fold cross-validation for five different iterations is represented in Fig. 6.

The dataset configuration and division of data in different classes of plant leave images is given in Table 1. A total of 25,493 plant leave images are collected. A total of 2548 test images are separated out as unseen images and remaining images in training and validation set are 5-fold cross-validated in which 4577 images taken for each fold of cross validation. There are different 4577 images in each fold of cross-validation.

All images in the validation set and unseen test images have been employed to evaluate the trained dense deep learning model. Evaluation is done in different parameters such as true positive (TP), true negative (TN), false positive (FP), false negative (FN), accuracy, precision, recall, and F1-score. TP are correct data labels which were predicted correctly with respect to the ground truth. FP are those negative data labels which have been predicted wrong and categorized into a different category of image label. TN are those negative data samples which have been accurately predicted. FN are those positive data labels which were predicted wrong. The different parameters which were used for evaluation can be computed as given below:

Ground Truth ↓ / Predictions →	Apple Black Rot	Apple Cedar Rust	Apple healthy	Apple Scab	Bean angular leaf spot	Bean Healthy	Bean Rust	Citrus Black Spot	Citrus Canker	Citrus Greening	Citrus Healthy	Potato Early Blight	Potato healthy	Potato Late Blight	Rice Bacterial Leaf Blight	Rice Brown Spot	Rice Leaf Smut	Tomato Bacterial Spot	Tomato Early Blight	Tomato healthy	Tomato Late Blight	Tomato Leaf Mold	Tomato Mosaic Virus	Tomato Septoria Leaf Spot	Tomato Two Spotted Spider Mite	Tomato Target Spot	Tomato Yellow Leaf Curl Virus
Apple Black Rot	111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apple Cedar Rust	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apple healthy	0	0	296	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apple Scab	0	0	0	113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bean angular leaf spot	0	0	0	0	74.8	0	2.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bean Healthy	0	0	0	0	0.2	75.6	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bean Rust	0	0	0	0	1.8	0	76.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Citrus Black Spot	0	0	0	0	0	0	0	26.4	0	3.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Citrus Canker	0	0	0	0	0	0	0	0.6	27.8	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Citrus Greening	0	0	0	0	0	0	0	3.8	0.2	31.8	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Citrus Healthy	0	0	0	0	0	0	0	0	0	0.2	9.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Potato Early Blight	0	0	0	0	0	0	0	0	0	0	0	180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Potato healthy	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Potato Late Blight	0	0	0	0	0	0	0	0	0	0	0	0	0	179.8	0	0	0	0	0	0	0.2	0	0	0	0	0	0
Rice Bacterial Leaf Blight	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0
Rice Brown Spot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6.2	0.8	0	0	0	0	0	0	0	0	0	0
Rice Leaf Smut	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	6.4	0	0	0	0	0	0	0	0	0	0
Tomato Bacterial Spot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	381.8	0	0	0	0	0	0	0.2	0	0
Tomato Early Blight	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	178.8	0	0.4	0	0	0.4	0	0.2	0
Tomato healthy	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	285.6	0.2	0	0	0	0	0	0
Tomato Late Blight	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0.4	342.2	0	0	0	0	0	0
Tomato Leaf Mold	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	171	0	0	0	0	0
Tomato Mosaic Virus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	0	0	0	0
Tomato Septoria Leaf Spot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	318	0	0	0
Tomato Two Spotted Spider Mite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	300.6	0.4	0
Tomato Target Spot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0	0.4	0	0	0	0	251.4	0
Tomato Yellow Leaf Curl Virus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	963.6

Fig. 7. Averaged 5-fold cross validation results.

Table 2
Performance evaluation on the test dataset.

Class	Specificity (%)	Recall (%)	Precision (%)	F1-Score (%)
Apple Black Rot	100.00	100.00	100.00	100.00
Apple Cedar Rust	100.00	100.00	100.00	100.00
Apple healthy	100.00	100.00	100.00	100.00
Apple Scab	100.00	100.00	100.00	100.00
Bean angular leaf spot	100.00	97.67	100.00	98.82
Bean Healthy	100.00	100.00	100.00	100.00
Bean Rust	99.96	100.00	97.80	98.88
Citrus Black Spot	99.85	65.88	74.81	69.84
Citrus Canker	99.92	96.25	88.50	92.19
Citrus Greening	99.83	81.00	79.71	80.21
Citrus Healthy	100.00	100.00	100.00	100.00
Potato Early Blight	100.00	100.00	100.00	100.00
Potato healthy	100.00	100.00	100.00	100.00
Potato Late Blight	100.00	100.00	100.00	100.00
Rice Bacterial Leaf Blight	99.98	45.00	85.00	54.81
Rice Brown Spot	99.92	90.00	68.83	77.11
Rice Leaf Smut	99.94	65.00	67.33	63.43
Tomato Bacterial Spot	99.96	100.00	99.53	99.77
Tomato Early Blight	99.98	97.00	99.59	98.28
Tomato healthy	100.00	100.00	100.00	100.00
Tomato Late Blight	99.94	99.79	99.27	99.53
Tomato Leaf Mold	100.00	99.58	100.00	99.79
Tomato Mosaic Virus	100.00	100.00	100.00	100.00
Tomato Septoria Leaf Spot	100.00	100.00	100.00	100.00
Tomato Two Spotted Spider Mite	100.00	100.00	100.00	100.00
Tomato Target Spot	99.95	100.00	99.15	99.57
Tomato Yellow Leaf Curl Virus	100.00	100.00	100.00	100.00
Average	99.97	93.97	94.80	93.79

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{\text{Total Number of Leaves Images}} \tag{1}$$

$$\text{Specificity} = \frac{(\text{TN}}{(\text{TN} + \text{FP})} \tag{2}$$

$$\text{Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})} \tag{3}$$

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})} \tag{4}$$

$$\text{F1 Score} = 2 \times \frac{(\text{Precison} \times \text{Recall})}{(\text{Precison} + \text{Recall})} \tag{5}$$

Confusion matrices are also used for the proper evaluation of the data in which ground truth and predicted labels are represented. The diagonal elements are representing the true positives and are directly proportional to the overall accuracy of the trained model. The confusion matrix is made for each fold of cross-validation. The average confusion matrix of all five folds of cross-validation is given in Fig. 7 for all 27 different classes. It is shown that the proposed model has shown highly accurate results on the validation data set. The trained model achieved the accuracies of 99.41%, 99.73%, 99.73%, 99.67%, and 99.34% for fold-1, fold-2, fold-3, fold-4 and fold-5, respectively. It achieved an average cross-validation accuracy of 99.58% on different folds.

After performing the 5-fold cross-validation, the trained model for each fold of cross-validation is further evaluated on 2548 unseen test plant leaves images of different categories. The specificity, recall, precision, and F1-score for each class is presented in Table 2. The average value of specificity, recall, precision, F1-score is obtained as 99.97%, 93.97%, 94.80%, and 93.79%, respectively. The overall average accuracy of 99.199% is obtained on test dataset by the trained deep learning model.

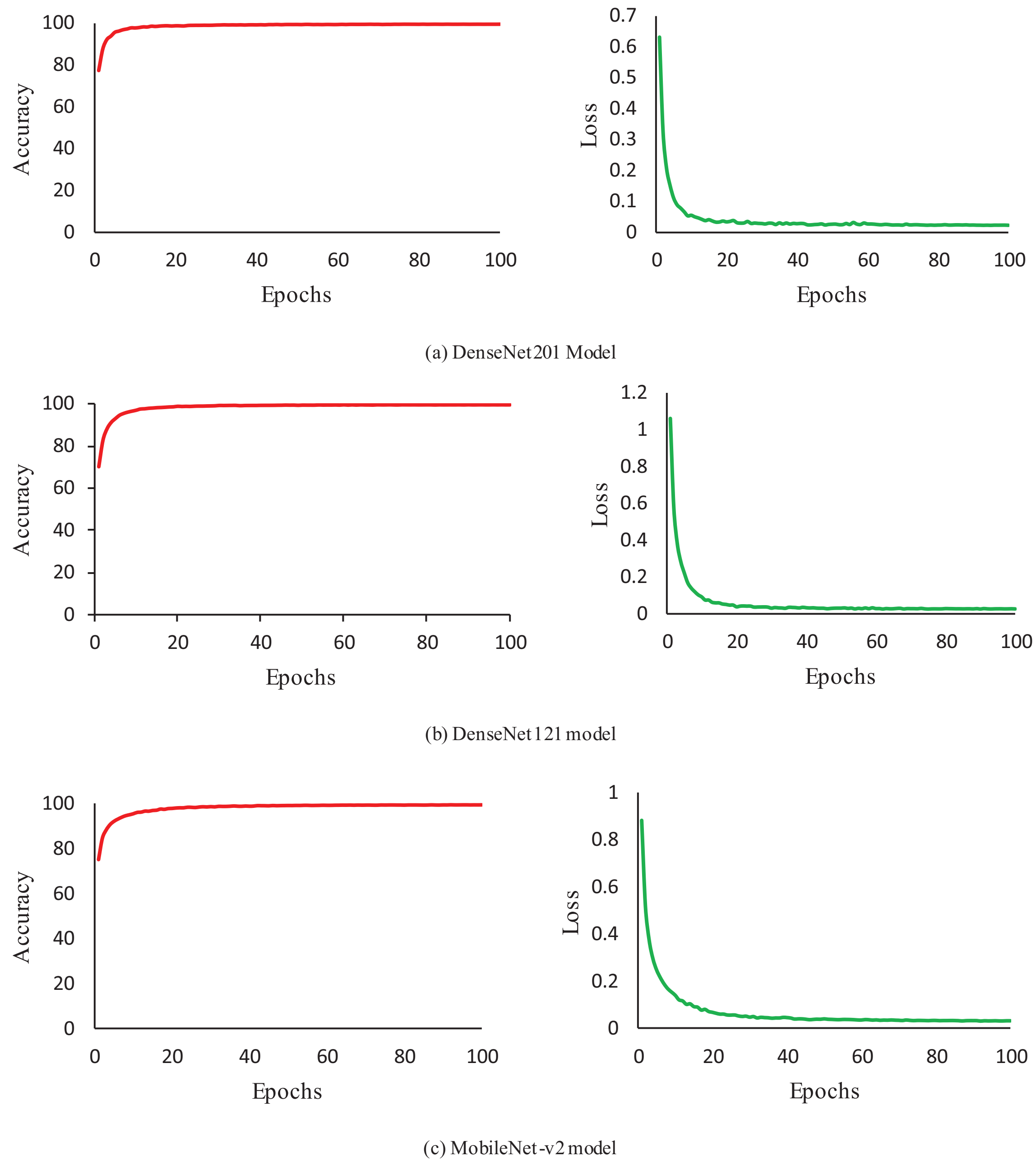
MobileNet-v2 (Koonce and Koonce, 2021) and DenseNet121 (Huang et al., 2017) deep learning models are also trained on the same data configuration for 100 number of epochs. The average accuracy and loss value for each epoch to perform 5-fold cross-validation using different models are calculated. The plot of average accuracy and loss for each trained model for 100 number of epochs is shown in Fig.8.

Different performance parameters which were calculated on the testing set of unseen images is given in Table 3 and trained DenseNet201 model outperformed in comparison of the performance with other models.

Table 4 signifies the computation time taken by different model on same set of images used in the proposed work. The MobileNet-v2 deep neural network gives high frame processing rate. The DenseNet-201 took 368.498 s to process 4000 plant leave images of dimensions 256 $\times$ 256 pixels with framerate of 10.85 frames per seconds in system with GPU (NVIDIA Quadro P600, 24 GB graphics memory).

The proposed work is compared with the relevant works which has proved their significance in the field of plant disease detection and classification. The comparative table is given in Table 5. The proposed approach achieved the 99.19% accuracy using a dense network trained with a large plant leave image database of six crops in 27 different categories having laboratory and on-field images with wide variety.

Thus, these kind of system which are giving the high accuracy and real-time performance on a dataset having intra-class and inter-class variation, can be used to diagnose the plant disease. Development of plant disease detection and classification system can be done in perspective of remote monitoring of the crop to take timely decision and healthy crop growth.



(a) DenseNet201 Model

(b) DenseNet121 model

(c) MobileNet-v2 model

Fig. 8. Average accuracy and loss for epoch on 5-fold cross validation for three different models.

Table 3
Performance comparison with other state-of-the-art models.

Models	Specificity (%)	Recall (%)	Precision (%)	F1-Score (%)	Accuracy (%)
DenseNet 121	99.97	92.79	93.33	92.83	99.20
MobileNet-v2	99.96	93.03	93.21	92.99	99.03
DenseNet 201	99.97	93.97	94.80	93.79	99.25

Table 4
Computational time to process different images.

S.N.	Model	Total Images	Image Dimensions	Total Computation Time in seconds	Computational Time for single Image in seconds	Frames/Second
1	DenseNet 121	4000	256 × 256 pixels	211.237	0.0528	18.936
2	MobileNet-v2	4000	256 × 256 pixels	87.3515	0.0218	45.792
3	DenseNet 201	4000	256 × 256 pixels	368.498	0.0921	10.855

Table 5
Comparison with other plant disease detection and classification works.

Reference	Research Objective	Images in Dataset	Images in Laboratory conditions /on-field Conditions	Number of classes	Technique	Average accuracy
Sujatha et al. (2021)	Citrus Plant disease Detection	609	Laboratory	5	Machine learning and deep Learning models	76.8% -89.5%
Chen et al. (2021)	Cognitive vision based plant disease detection	500	Both	4	Image processing, enhanced artificial neural network, CNN	93.75%
Chen et al. (2020)	Image-based Rice and Maize plant disease identification	966	On-field	9	Deep transfer learning using VGGNet	92.00%
Goncharov et al. (2020)	Disease identification through leaf images of grape, corn, and wheat plant	611	On-field	15	Deep Siamese network	95.7%
Coulibaly et al. (2019)	Recognition of mildew disease in pearl millet crop	711	On-field	2	Deep transfer learning, VGG-16	95.00%,
Geetharamani and Arun Pandian (2019)	Identification of plant leaf diseases	55,448	Laboratory	39	9-layered deep convolutional neural network	96.46%
Joshi et al. (2021)	Plant disease detection in *Vigna mungo* crop	3031	Laboratory	3	VirLeafNet	97.403%
Nanehkaran et al. (2020)	Recognition of plant leaf diseases in Maize, Cucumber and Rice crops	1000	On-field	13	K-means clustering and CNN model	75.59%
Bi et al. (2020)	Apple leaf disease detection	334	On-field	3	Mobile-Net Model	77.65%
Proposed Method	Plant disease identification in six different crops	25,493	Both	27	Dense Convolutional Neural network	99.19%

4. Conclusion

The task of plant disease detection and their classification using digital images is a quite challenging. Hence, timely diagnosis of the plant disease is very essential to take the necessary action by farmers and plant pathologists. A total of 27 different kinds of plant leaves images are used in the proposed work for this purpose. Considered plant images were diverse and had both lab-view and live field images of the plants of various categories with natural variability to develop a robust model. The deep learning dense model is trained with different images of various categories. Five-fold cross-validation is used for proper evaluation of the model which were further tested on the unseen images of the testing set. The proposed model achieved the average cross-validation accuracy of 99.58% and average testing accuracy of 99.199% which proved its utility to detect the plant diseases and their classification. In the future work, other plant leaf images will be considered to expand plant leaf dataset with more diversity which will help the trained model in difficult environments.

Declaration of Competing Interest

The authors have no known personal relationships or competing financial interests that could have appeared to influence the reported work.

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