AN EFFICIENT PLANT LEAF DISEASE DETECTION MODEL USING SHALLOW-CONVNET

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(Received 8th Feb 2023; accepted 27th Apr 2023)

Abstract. In recent time, deep convolution neural networks have seen an exponential growth in their use in phytopathology. However, deep convolutional neural network needs a lot of processing power because of its intricate structure consisting of a large stack of layers. In this article, authors have introduced a novel lightweight sequential CNN architecture-Shallow-ConvNet for the diagnosis of leaf diseases. The suggested approach contains fewer layers and around 75% fewer attributes than pre-trained CNN-based approaches. For the experiments and performance evaluation, authors utilized a hybrid dataset consisting of 7166 images of tomato & potato with real field and laboratory-conditions affected with early and late blight diseases. The performance of the proposed architecture is compared against three recently priorly trained CNN architectures such as ResNet-50, VGG-16, and VGG-19. The average accuracy percentage reported by the proposed architecture is 97.22, and the time consumed in training is also much better. The experimental findings demonstrate that the suggested approach outperforms the recent existing trained CNN approaches and has a very less number of layers and parameters which significantly reduces the number of computing resources and time needed to train the model which could be a better choice for real-time plant disease diagnosis applications on resource constrained computing devices.
Keywords: *leaf disease detection, deep learning, transfer learning, light-weight CNN, hybrid dataset*

Introduction

Agriculture production has a significant impact on the Indian economy, and as per statistics reported in the study (Katoch and Oerke, 2012), plant illnesses account for roughly 16% of worldwide agricultural production loss. Losses caused by crop diseases are expected to reach about 50% for wheat and vegetables across the world. Among all agricultural production, vegetables like Potato and tomato are at the top among the leading crops following rice, maize, and wheat, and are especially important ingredients of our food or diet system (Katoch, 2012). Crop infection lowers crop productivity and quality, which has detrimental impacts on both the economy and the wellness of the living organisms that utilize them. The growth of plants can be impacted by a wide range of biotic and abiotic variables, which can also lead to different plant diseases. Crop diseases are mostly brought on by biotic elements including pathogens, pests, and weeds. Conventional crop disease monitoring and diagnosis methods, in which agricultural specialists were brought in to evaluate and diagnose crop diseases, were long-lasting and required loads of arduous strength on the part of the agricultural workers, resulting in delays in prescribed corrective actions on the field. In the past few years, some scholars have extensively utilized computer vision-based techniques like image processing, machine learning, and deep learning in the field of crop disease detection & diagnosis,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

irrigation automation, smart warehouses, crop recommendation, and automatic greenhouse monitoring and control, and many other agricultural subdomains as well. Farmers who typically reside in distant and rural locations and lack the competence to identify plant diseases might greatly benefit from automatic plant disease diagnosis using the visual indicators of infection (Chouhan et al., 2020). Various image processing techniques, including segmentation, filtering, and picture restoration, had been used by the preceding systems for feature extraction and image classification. To diagnose plant diseases more accurately and quickly, modern computer vision-based methods combine image processing with intelligent systems like deep learning and machine learning.

In the preceding decade, various researchers proposed a variety of models based on machine learning and deep learning for the diagnosis and categorization of plant pathogens. CNNs or its derivatives were used in most current research projects to classify plant leaf diseases due to their simplicity of use and performance in picture classification challenges (Huang et al., 2019). This study categorized 19 illnesses of eight plant species including tomato and potato, using four priorly trained CNN models: AlexNet, VGG16, Inception V3, and ResNet repository and evaluated by comparing the results to priorly trained deep from the AI challenger dataset derived using the plant village dataset. The proposed work also utilized U-Net for segmenting the lesion area of leaves from the rest of the complex background which significantly affects the performances of the classifiers being applied. Verma et al. (2020a) investigated how to use capsule networks to categorize late and early blight illnesses in potato plants on a dataset from the plant village and evaluated the results by comparing them with deep learning models including ResNet50, VGG16, and GoggleNet. Gadekallu et al. (2021) proposed a machine learning-based architecture for identifying and classifying nine tomato diseases from the plant village dataset. The study utilized a hybrid of Principal Component Analysis (PCA) for feature dimension diminution and the Whale Optimization algorithm for the selection of the best features that are fed to the deep learning classifier for further tomato plant leaf disease classification. PCA algorithm helped to avoid less significant disease descriptors of tomato leaf diseases while Whale optimization algorithm chooses the best features from PCA output features that are further utilized by the deep learning-based classifier. This hybrid approach helps to reduce the number of input features while focusing on optimal features. Ashwinkumar et al. (2021) proposed an optimal mobile network CNN (OMNCNN) a system for classifying tomato plant diseases on PlantDoc dataset. The suggested model consists segmentation using Kapur’s thresholding, feature extraction using MNCNN, parameter optimization through EPO, and classification from ELM. The hyperparameters of the OMNCNN model are adjusted as part of the EPO-based hyperparameter optimization to maximize the improvement in classifier performance. The application of CNN based architecture automate the feature extraction process and help to simplify image classification task and to improve the performances of the classifiers as well. The majority of new research that used deep learning to find and classify plant diseases used deep CNNs which has very complex structures having many layers and parameters which requires heavy computing resources and large time for training the model. In this study, authors proposed a Shallow-ConvNet, a light-weight CNN model which has very a fewer layers and attributes than conventional CNN models such as VGG-16, VGG-19, and ResNet-50, which minimises computational resource needs and training time and could be a better choice for real-time based plant leaf disease diagnosis system on resource constrained computational devices.

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DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

The Remainder of the work is organized as specified: in Section 2, we outlined a brief about background concepts including CNN, activation functions, and optimizers. Section 3 summarized the literature being conducted related the study. Sections 4 and 5 present the materials and technique employed, as well as the results discussion. Finally, in section 6, the study's findings are presented.

Background

Convolution neural network (CNN)

Convolutional neural networks fall under the category of deep neural network models and have regularized multilayer perception. It is superior to hierarchical patterns and facilitates the use of basic patterns to solve complicated patterns. Its applications span a wide range, including image classification, recommendation systems, and natural language recognition. A typical CNN model consists of a series of layers and changes one activation volume to another with the use of differentiable functions. The primary building blocks of a CNN model as shown in *Figure 1*, includes layers like convolution, pooling, and fully connected. CNN's fundamental building piece is the convolution layer. To connect the kernel and the limited area, it mostly executes dot operations. The next important layer of CNN model is the Pooling layer. The key benefit of the Pooling layer is that it minimizes computation and spatial size by using fewer weights. Activation function is added to the network to inject nonlinearity into the convolution process, which is typically linear and comes just after the convolution layer (Gokulnath and Usha Devi, 2021).

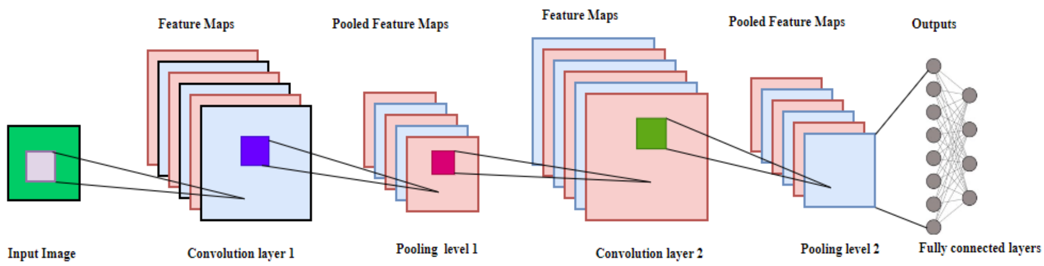

Figure 1. *A typical CNN architecture with convolution, pooling, and fully connected layers*

Activation function

The activation function's primary usage in an artificial neural network (ANN) is to incorporate the non-linearity among intermediate layers of the Deep learning model because the output of a linear function ($f(x) = x$) will not be limited to a specific range. For an instance, a neural network is denoted with (Ai, Zi) where Ai and Wi are the inputs and weights applied to the i^{th} layer of the Deep learning model and $f(Ai)$ is the input function that was sent to the network's output. This input function might be used as input for any additional layers or the result (Nwankpa et al., 2018). The various categories of most commonly used activation functions are detailed in *Table 1*.

Optimizer

There are various strategies for reducing the objective function, or loss function. For deep learning applications, selecting an appropriate optimizer is a crucial task. The

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optimization strategy selected in a deep learning application influences the model's ultimate prediction performance and training pace as well. There exist a variety of optimizers in literature, here we have given a brief introduction about some of the optimizers (Choi et al., 2019).

Stochastic gradient descent (SGD)

The Stochastic Gradient Descent algorithm minimizes the objective function, which is expressed as the sum of differentiable functions. With its unbiased random sample selection and computation of the gradient to update parameters for each training example, SGD decreases computing cost at each step. SGD might result in significant changes of the loss function because of the frequent updates with a high variance.

Adagrad

The learning rate is adjusted in accordance with the parameters, with more substantial updates (high rates of learning) being made for attributes related to features that occur infrequently and minor updates (low rates of learning) being made for attributes connected to features that occur frequently. Its ability to eliminate the requirement for manual learning rate adjustment is one of its main benefits.

Adadelta

It is a progression of the Adagrad approach. It attempts to decrease its monotonically falling learning rate by limiting the window of collected previous gradients to a predetermined size rather than gathering all prior squared gradients.

RMSprop

It is an evolutionary optimization approach meant to address Adagrad's sharply declining learning rates. It subtracts the rate of learning from the arithmetic mean of the squared gradients, which decays exponentially.

Table 1. *Activation functions with their equation and range values*

S. No.	Function	Function expression	Range
1	Linear	$f(x) = x$	(-∞, ∞)
2	Binary step function	$f(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases}$	(0, 1)
3	Sigmoid	$f(x) = \frac{1}{1+e^{-x}}$	(0, 1)
4	Tanh	$\tanh(x) = \frac{[(e]^{x} - e^{-x})}{e^{x} + e^{x}}$	(-1, 1)
5	ReLU	$f(x) = Max(0, x)$	(0, ∞)
6	Leaky ReLU	$f(x) = \begin{cases} 0.01, & x < 0 \\ 1, & x \geq 0 \end{cases}$	(-∞, ∞)
7	Swish	$f(x) = x * Sigmoid(x)$	(-∞, ∞)
8	SoftMax	$f(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$	(0, 1)

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Adaptive moment estimation (Adam)

This strategy utilizes the benefits of the Adagrad and RMSprop techniques. Here, each parameter's adaptive learning rates are calculated. In a manner like the momentum approach, it preserves an exponentially declining average of previous squared gradients as well as a previous gradient average.

Literature review

A summary of findings in recent studies on plant leaf disease identification and categorization by utilizing computer vision-based techniques, is provided in this section. Most of the studies that we listed here have utilized deep learning-based architecture for feature automatic feature extraction and followed by a classifier. Wang et al., (2017) presented the application of priorly trained approaches: VGG, inception-v3, and ResNet-50 with hyperparameter tunning and a deep learning model trained from scratch for finding the severity of apple black rot on leaves. For experimental reasons, this study made use of the plant village dataset. On the laboratory picture datasets, many models were able to classify images with an accuracy as high as 80%–90%, which is not very good. Amara et al. (2017) utilized LeNet on plant village dataset images for the purpose of banana leaves' disease (black Sigatoka and speckle) classification and the performance was evaluated using precision, accuracy, and f1-score. Hassanien et al. (2017) first segmented the tomato diseased images using morphological operation and then moth-flame optimization with rough set theory was utilized for feature reduction & selection from the segmented images. Finally, disease classification was carried out using the SVM classifier as per the results presented, the moth flame with rough set showcased better classification accuracy against Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) with rough set techniques. Ma et al. (2018) applied DNN classifier to a mix of real fields and augmented images of cucumbers having complex backgrounds. Prior to applying deep learning neural network (DNN) for disease classification, authors initially conducted morphological operation for background removal. ML-based models such Random Forest and Support Vector Machines (SVM) as well as the priorly trained model AlexNet were employed to compare the performance of the suggested model. In comparison to the balanced dataset, the results showed that DNN performed better on the imbalanced dataset. Additionally, AlexNet's classification accuracy was superior to DNN's in comparison. Khan et al. (2018) described the use of support vector machines (SVM) to categorize the illnesses of apple and banana leaves. The study first performed correlation coefficient-based segmentation on diseased leaf images of apples and bananas collected from the plant village dataset and afterward VGG-16 and Caffe-AlexNet were applied for automatic feature extraction. The feature maps generated by VGG-16 and Caffe-AlexNet CNN models were supplied to the SVM for further disease categorization. The classification accuracy of the proposed approach on laboratory-conditioned images is not quite promising. Zhang et al. (2018) proposed a disease detection and classification model for real field images of apples and cucumbers. The authors initially adopted k-means clustering with superpixel to segment the lesion region in the tainted images, and then, context-aware SVM (C-SVM) was used for classification. The number of image samples used for experimental analysis was very less (150 in each class) which seems not enough for training the model and thus may affect the performance well (Ferentinos, 2018). In the study, priorly trained models like Overfeat, AlexNet, GoogleNet, and VGG were

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considered for both identifying and categorizing 58 different plant ailment kinds that affect 25 different crops captured under real field as well as laboratory conditions. The major issue with the proposed approach was performance degradation of around 25%-30% on test data chosen from a different dataset. Zhang et al. (2019) proposed an image segmentation-based disease classification method for real field images of cucumber leaves. The authors first did similar pixel clustering to form a superpixel and then applied expectation maximization (EM) with superpixel for lesion segmentation and categorization of cucumber leaf diseases. In comparison to EM algorithms, fuzzy c-means, and k-means, the findings are more accurate in terms of categorization accuracy. Agarwal et al. (2020) proposed a shallow deep learning model for tomato ailment identification and categorization from the plant village dataset and compared the results with three priorly trained models like VGG-16, Inception V3, and MobileNet. As per the results presented in the study, there was a variation of around 25% in accuracy and the average accuracy was 91.2% for nine potato leaf diseases. Verma et al. (2020b) utilized three pre-trained models-AlexNet, SqueezeNet, and Inception V3 for the Degree of Severity assessment of tomato leaves with affected by late blight disease. Tomato images (both healthy and afflicted) were collected from the plant village dataset. The study utilized pre-trained models in dual roles-one to extract features and the other to classify the data with multi-class SVM. Chowdhury et al. (2021) employed the pre-trained model EfficientNet B0, B4, and B7 versions for categorizing nine tomato leaf ailments from the plant village dataset. The authors first applied U-Net and improved U-Net for segmenting the diseased portion of the leaf from the rest of the leaf and then utilized these segments for further feature extraction and classification. Further, the authors also outlined a summary of several recent efforts that use deep learning to detect and categorize diseases in crop leaves (*Table 2*).

Table 2. *A comparison of deep learning-based techniques for identifying plant leaf diseases*

Ref.	Crop	Model	Pre-processing technique	Dataset type	Performance	Approach
Wang et al., 2017	Apple	CNN	Sample-wise normalization	Plant village dataset	90.4%	Transfer learning as well as training from scratch
Hassanien et al., 2017	Tomato	SVM with Moth-flame optimization	Background removal with the morphological operation	UCI machine learning repository	90.5%	Training from scratch
Ma et al., 2018	Cucumber	Deep CNN	Image segmentation & augmentation	Real field images	93.4%	Training from scratch
Khan et al., 2018	Apple, banana	Pre-trained CNN with SVM	Segmentation and Genetic Algorithm for feature selection	Plant village dataset & CASC-IFW dataset	98.6%	Training from scratch
Zhang et al., 2018	Apple, cucumber	Context-aware SVM	K-means clustering with super pixel for segmentation	Real field images	92%	Training from scratch
Ferentinos, 2018	Multiple crops like apple, banana, cucumber etc.	Pre-trained CNNs	Resizing and normalization	Laboratory and real field images	99.48%	Transfer learning
Agarwal et al., 2020	Tomato	CNN	Resizing and data augmentation	Plant village dataset	91.2%	Training from scratch
Verma et al., 2020b	Tomato	Pre-trained CNN With multi-class SVM	Resizing	Plant village dataset	93.4%	Transfer learning as well as training from scratch
Chowdhury et al., 2021	Tomato	Pre-trained CNN	Normalization, Augmentation, and segmentation using U-Net & modified U-Net	Plant village dataset	99.89%	Transfer learning

APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH 21(4):3193-3211.
http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

Wspanialy and Moussa, 2020	Tomato	DNN with ResNet50 as a baseline model	Segmentation using U-Net	Plant village dataset	98.7%	Training from scratch
Abbas et al., 2021	Tomato	Pre-trained CNN	Augmentation using C-GAN and Segmentation using U-Net	Plant village dataset	99.51%	Transfer learning
Gao et al., 2021	Potato	DNN	Cropping, Segmentation using SegNet	Real field images	99.9%	Training from scratch
Bhujel et al., 2022a	Tomato	CNN (ResNet with attention mechanism)	Resizing, data augmentation	Plant village dataset and real field images from green house	99.69%	Training from scratch
Elaraby et al., 2022	Five crops (wheat, cotton, grape, corn, cucumber)	Pre-trained CNN with PSO (particle swarm optimization)	Resizing, data augmentation	Real field images	98.83%	Transfer learning
Elfatimi et al., 2022	Beans	Pre-trained CNN with different optimizers	Resizing	Public image dataset	99.9%	Transfer learning
Singh et al., 2022	Apple, corn, potato, tomato, and rice	CNN with Random Forest and Bayesian optimized classifier	Using the histogram of orient (HOG) and Gray-level co-occurrence matrices, image pre-processing is used to retrieve colour and texture information (GLCM)	Plant village dataset	96.1%	Training from scratch
Hassan et al., 2021b	14 different crops	Pre-trained CNN with depth separable convolution	Resizing	Plant village dataset	99.56%	Transfer learning
Sun et al., 2021	Apple	Light-weight CNN (MEAN-(Mobile End AppleNet block)-with SSD (Single-shot multibox detection algorithm)	Augmentation and annotation	AppleDisease5 Dataset: a mix of Real field and real field apple images	97.07%	Training from scratch
Lin et al., 2022	Grape	Light weight CNN with residual blocks, Residual Feature Fusion Blocks (RFFBs), and convolution block attention modules	Augmentation	AI challenger 2018 dataset	86.29%	Training from scratch
Kumar et al., 2023	Multiple crops	Hybrid random forest multiclass SVM	Image segmentation using Fuzzy C-means	Plant Village dataset	98.3%	Training from scratch
Kaya and Gürsoy, 2023	Multiple crops with 38 classes	Multi-headed Dense-Net	Image fusion and segmentation	Plant village dataset	98.17%	Training from scratch
Yong et al., 2023	Oil palm	Pre-trained CNN	Image segmentation	Hyperspectral images of oil palm	91.23%	Transfer learning
Bhujel et al., 2022b	Tomato	Light-weight CNN with attention modules	Resizing, rescaling, and augmentation	Plant village dataset	99.69%	Training from scratch
Hassan et al., 2021a	Corn, tomato, potato	Shallow VGG with Xgboost and Random Forest	Resizing, filtering, rotation, flipping	Plant village dataset for tomato and potato, public dataset for corn	97.36%	Training from scratch

Findings from literature

The text encapsulated in literature review section and summarized (*Table 2*) the recent research (n = 31 recent studies) in the field of deep learning-based approaches to plant disease diagnosis. Most of these studies (around 80%) have employed deep convolutional neural networks (*Fig. 2*), which have a large stack of convolution and fully connected layers resulting in a huge amount of parameters, or pre-trained CNNs.

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Training a Deep Learning model with a large number of parameters is time-consuming and burdensome on computing resources. These architectures with their thick stacks of layers are therefore impractical for lightweight computing environments like those found in mobile phone-based applications. Therefore, the authors of this study developed lightweight convolutional neural network (CNN) models for plant leaf disease detection. These CNN models have fewer layers and parameters than the most recent deep learning models, making them a potentially superior option for real-time plant disease diagnosis applications optimized for low-powered computing devices like mobile phones.

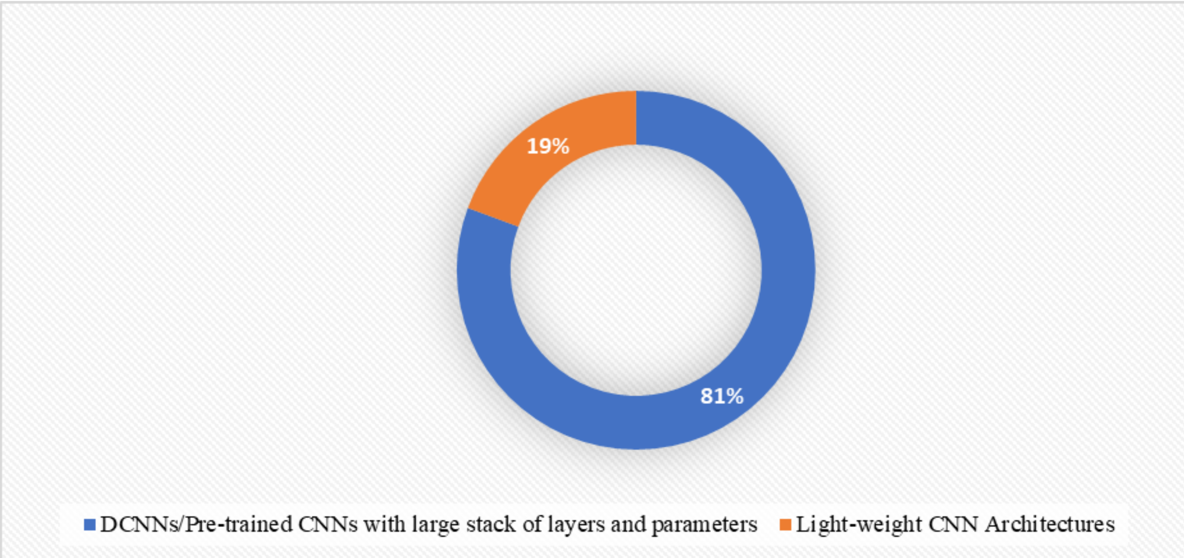

***Figure 2.** The ratio of DCNNs/Pre-trained CNNs based approaches and Light-weight CNN based approaches*

Materials and method

Dataset description

For empirically validation of proposed architecture, authors have utilized a hybrid dataset consisting of 717 real field images of tomato plants leaves infected with early & late blight diseases are captured with a Canon EOS 1500D camera with white background under the project- Application of IoT in Agriculture Sector sponsored by the Department of Science & Technology (DST) India, and remaining 6449 tomato & potato leaves infected with early blight, late blight, bacterial spot, and leaf mold diseases are taken from the plant village dataset. Hence a total of 7166 images (*Tables 3* and *4*) in a hybrid dataset are used for experimental purpose of proposed architecture. Snapshots of sample tomato and potato images of hybrid dataset are shown in *Figure 3*. Authors have taken 3998 and 1016 tomato leaf images and 1721 and 431 potato leaf images for training and validation, respectively. The pictures with various diseases and crop types (*Table 3*) that were selected for both validation and training purposes.

Proposed architectural model

Figure 4 depicts the suggested CNN model (shallow CNN) architecture, which comprises two convolution stages followed by a fully connected layer and output layer.

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The initial stage of convolution has two convolution layers each having 32 filters of 3×3 size. After the first stage convolution, max pooling (2, 2) is applied to the output feature maps of first convolution stage. In second convolution stage, there are five convolution layers of with different number of convolution filters, and after every convolution layer comes a max pool (2, 2) layer (see *Fig. 4*). After the second stage of convolution where convolutions and max pool operations are applied in alternate fashion, we have fully connected layer of size 512 and an output layer. We named the proposed model as *shallow-ConvNet* as it has much lesser convolution layers, fully connected layers, and total number of parameters (*Table 5; Figs. 5* and 6) as compared to existing trained models like VGG-16, VGG-19, ResNet-50, that we have considered under this study.

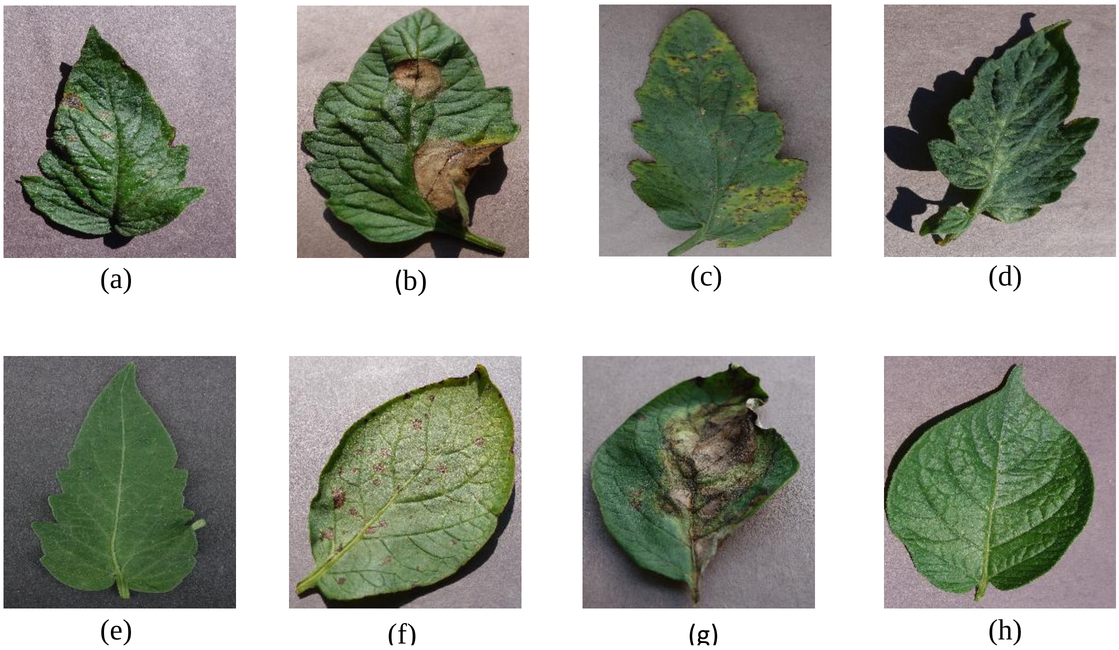

Figure 3. *Images of Tomato and Potato leaf samples from the hybrid dataset: (a) Tomato early blight (b) Tomato late blight (c) Tomato bacterial spot (d) Tomato leaf mold (e) Tomato healthy (f) Potato early blight (g) Potato late blight (h) Potato healthy*

Table 3. *Details of dataset images used for experimental purposes from hybrid dataset*

Crop type	Disease type	Training samples count	Validation samples count	Total sample count
Tomato	Early_blight	800	200	5014
	Late_blight	817	213	
	Bacterial_spot	804	203	
	Leaf_mold	761	191	
	Healthy	816	209	
Potato	Early_blight	800	200	2152
	Late_blight	800	200	
	Healthy	121	31	

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Table 4. *Disease-wise image count for experiments*

Disease wise image samples				Healthy images	Total images
Early blight	**Late blight**	**Bacterial spot**	**Leaf mold**		
2000	2030	1007	952	1177	7166

Table 5. *A comparison of the proposed model with VGG-16, VGG-19, and ResNet-50 models based on number of layers & parameters*

CNN Models	Convolution layers	Fully connected layers	Pooling layers	Total layers (except pooling layers)	Total no. of parameters
VGG-16	13	03	05	16	15,242,565
VGG-19	16	03	05	19	20,024,384
ResNet-50	48	01	02	49	24,638,339
Shallow-ConvNet	07	01	06	08	4,988,259

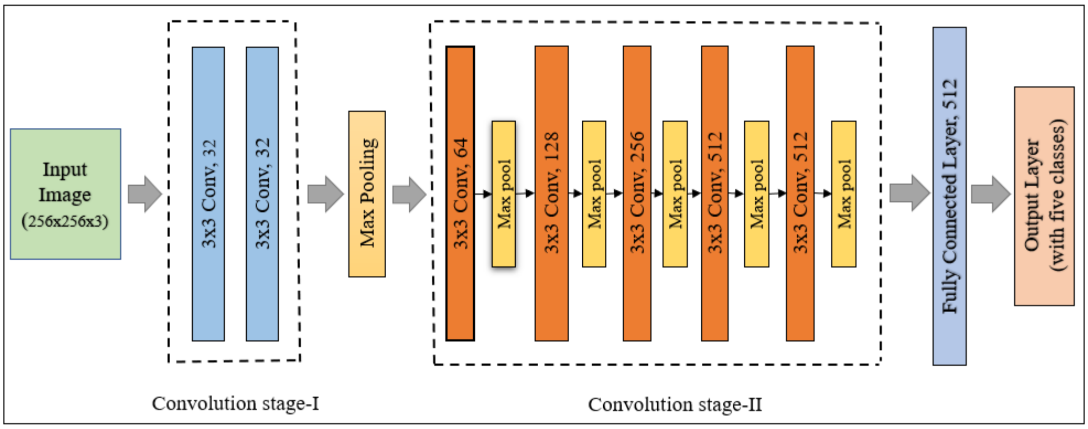

Figure 4. *Layered architecture of proposed model: Shallow-ConvNet*

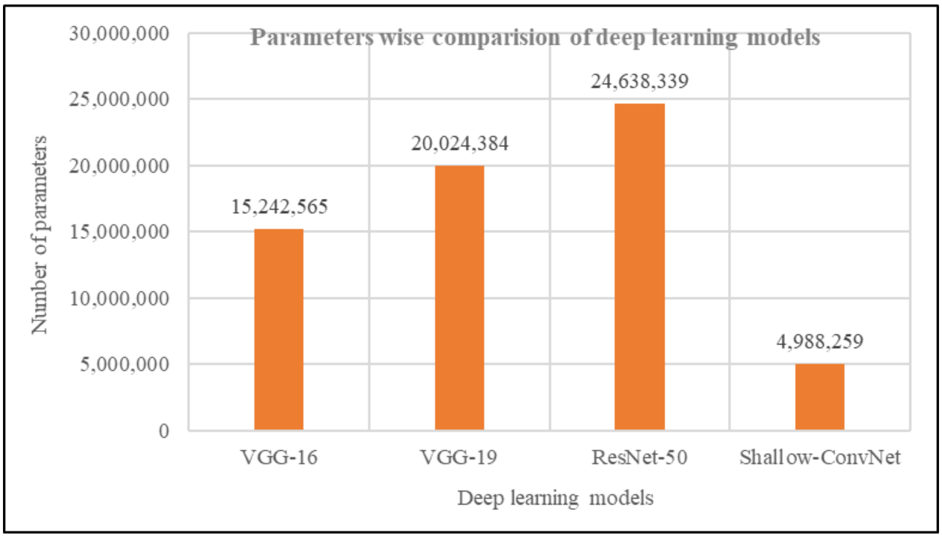

Figure 5. *Parameter wise comparison of proposed Shallow-ConvNet with VGG-16, VGG-19, & ResNet-50*

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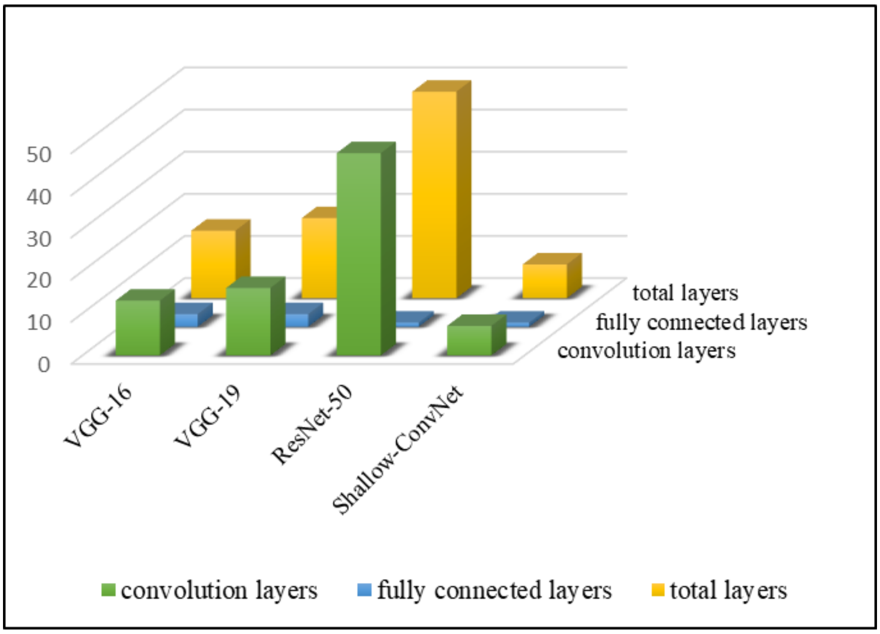

Figure 6. *Layer-wise comparison of CNN models*

The smaller number of layers in a deep learning model adds advantages like comparatively less trainable parameters, which optimizes response time and lowers model training complexities with significantly lower demand of computing resources.

Methodology

Figure 7 describes the methodology that have been adopted in this study. Firstly, authors have developed a hybrid dataset consisting real field leaf images of tomato plants affected with multiple illnesses like early blight, late blight, bacterial spots, leaf mold, and healthy as well captured with a Canon EOS 1500D camera with white background and potato leaf images having affected with early and lat blight diseases are taken from the plantvillage dataset- a public repository having huge collection of multiple crops image datasets. After the image acquisition, input datasets are pre-processed by applying augmentation and normalization technique to rescale the input features on a similar scale that help to enhance model performance and hasten model training. And thereafter, the datasets are partitioned into further subsets for feature learning and validating the model (80% and 20% respectively). The CNN predictive model is created once the dataset has been separated to allow for further forecasting. In this study, ResNet-50, VGG-16, and VGG-19 are three recent existing CNN architectures that the authors have chosen to evaluate and compare the performance of proposed light-weight CNN model- Shallow-ConvNet. The proposed Shallow-ConvNet is trained from scratch on both tomato and potato dataset separately. After the models' trainings, we have four trained models (three pre-trained and one trained from scratch) in hand for plant leaf disease classification task. After all pre-processing and model training are done, authors have evaluated proposed Shallow-ConvNet against three pre-trained models as aforementioned, using classification accuracy and loss metrices for the tomato and potato leaf images and results have been presented in next section (Results and discussion).

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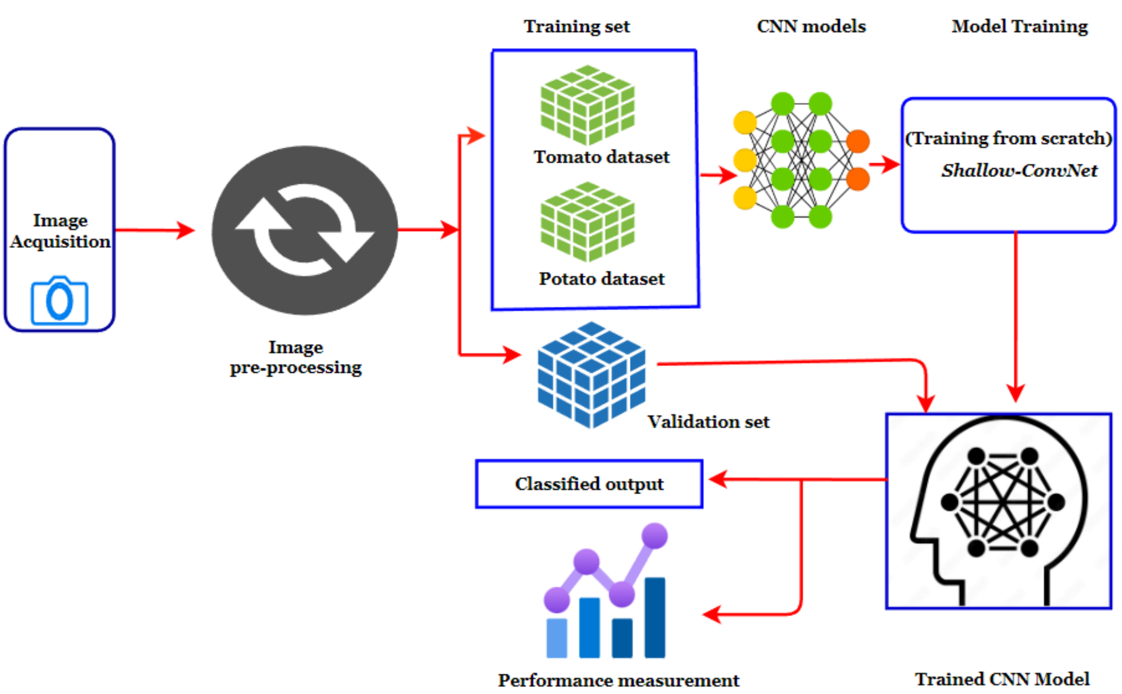

***Figure 7.** Methodology of the proposed work*

Results and discussion

The authors utilized pictures of tomato and potato leaves from the hybrid dataset (a mix of real field as well as laboratory conditioned images from plantvillage dataset) to evaluate the efficacy of the suggested approach. The number of samples for each disease and crop types that have been utilized for experiments is outlined in the dataset description (*Table 3*). Experiments were being conducted on Google Collaboratory (Colab), a GPU/TUP based a Google-provided framework with a 50 GB hard drive and 16 gigabytes of random-access memory. The details of other parameters/settings utilized during experiments is mentioned in *Table 6*. During the experiments, authors have evaluated four different CNN models- proposed model Shallow-ConvNet along with three recent existing models (ResNet-50, VGG-16, and VGG-19) on tomato and potato datasets having 4016 images samples with five different classes and 2152 image samples with three different classes, respectively. For performance evaluation of models, accuracy and loss function performance measures have been utilized.

Performance metrics

The following are two measures used to evaluate the performance of both proposed and existing pre-trained models:

a. Classification accuracy

Accuracy is a straightforward metric for evaluating the classifier's performance and it can be defined as the proportion of correct predictions relative to all predictions.

$$\text{Classification Accuracy} = \frac{True\ positive + True\ Negetive}{True\ Positive + False\ Positive + True\ Negetive + False\ Negetive}$$

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b. Categorical cross-entropy loss function (Lcce)

It is also called as a loss on the logarithmic or logistic scale. A score or loss is determined for each predicted class depending on how far its probability is from the actual expected value, which is either 0 or 1. The logarithmic structure of the penalty results in a high score for large discrepancies near 1 and a low score for little differences approaching toward 0. In order to fine-tune the model's parameters during training, cross-entropy loss is applied to the data. The goal is to achieve a minimal loss, with lesser losses indicating a superior model. The cross-entropy loss of a perfect model is zero. Mathematically, it is defined as *Equation 1:*

$$L_{cce} = -\sum_{i=0}^{n} t_i * \log(Pi) \quad \text{(Eq.1)}$$

where t_i is the true class label and Pi is the softmax probability for i^{th} class of interest among n total classes.

Table 6. *Details of hyperparameters utilized during experiments*

Epochs	Optimizer	Activation functions		Loss function	Learning rate	Batch size
		Intermediate layers	Output layer			
100	RMSprop	ReLU	Softmax	Categorical cross entropy	0.0001	64

The proposed model's effectiveness is evaluated using classification accuracy and loss over three pre-trained CNN models-ResNet-50, VGG-16, and VGG-1 on separate tomato and potato samples for 100 epochs. Accuracy and loss functions plots for tomato & potato crops resulted with different CNN models have been presented through *Figures 8–11*. The classification accuracies achieved with different CNN models (proposed as well as pre-trained) have been summarized (*Tables 7* and *8*) for tomato and potato crops, respectively. Authors also) have outlined the average accuracies obtained by different CNN models under this study (*Table 8*).

Table 7. *Comparison of classification accuracies for proposed and existing CNN models on tomato leaf images dataset*

Performance metrics	Epochs	Pre-trained models			Proposed model
		VGG1-16	VGG-19	ResNet-50	Shallow-ConvNet
Training accuracy (%)	100	99.75	100.0	69.30	99.97
Validation accuracy (%)		91.04	91.25	70.83	96.04

Table 8. *Comparison of classification accuracies for proposed and existing CNN models on potato leaf images dataset*

Performance metrics	epochs	Pre-trained models			Proposed model
		VGG1-16	VGG-19	ResNet-50	Shallow-ConvNet
Training accuracy (%)	100	100	100	89.25	100
Validation accuracy (%)	100	96.06	94.66	91.42	98.38

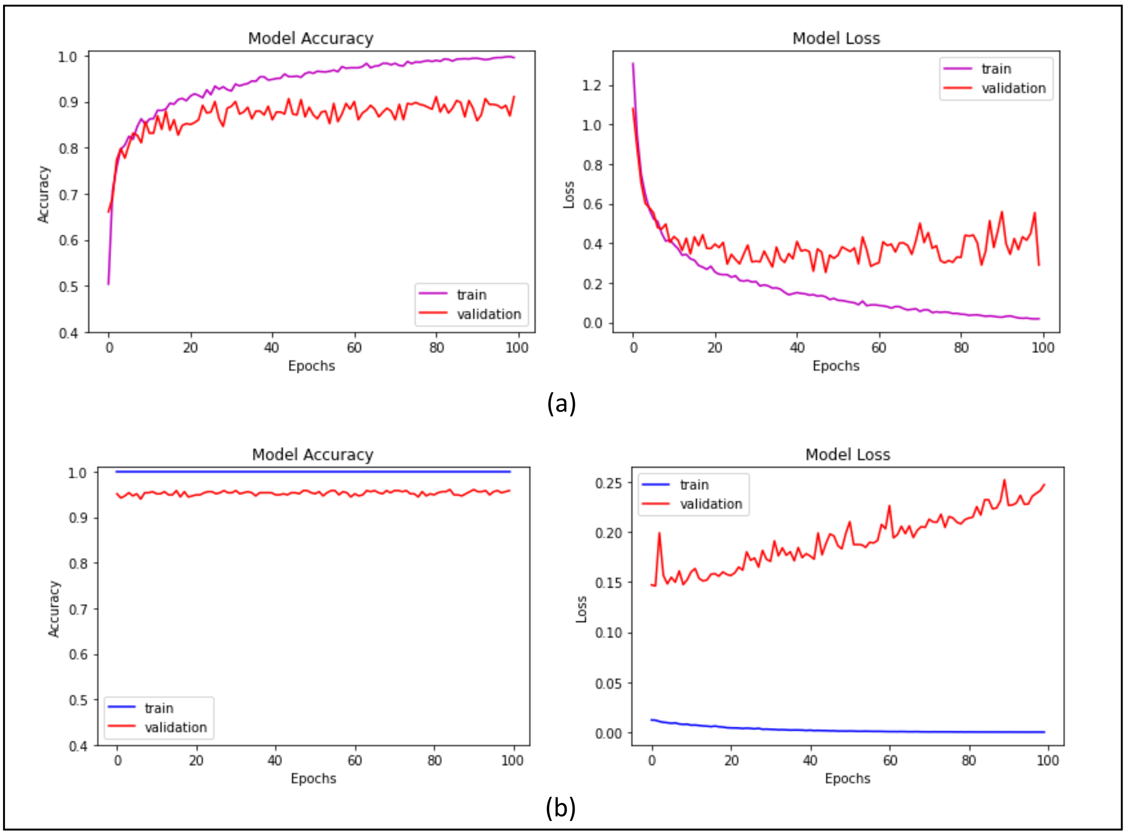

Figure 8. *VGG-16 classification accuracy & loss function plots for (a) tomato and (b) potato*

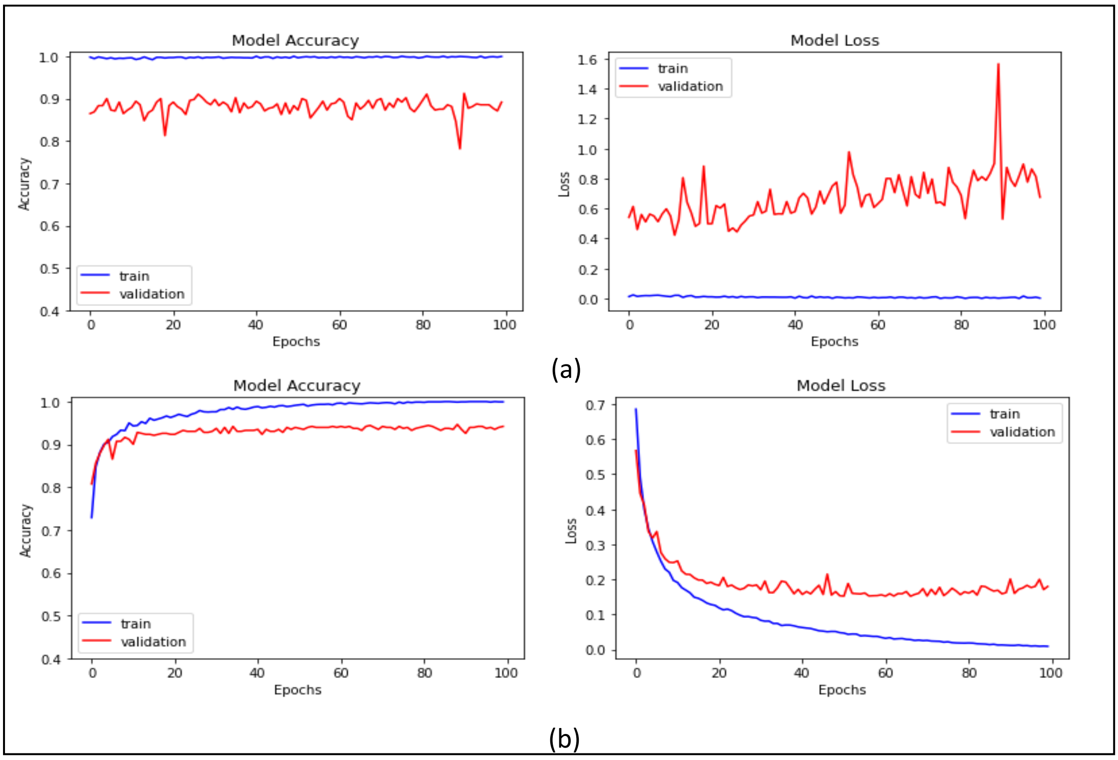

Figure 9. *VGG-19 classification accuracy & loss function plots for (a) tomato and (b) potato*

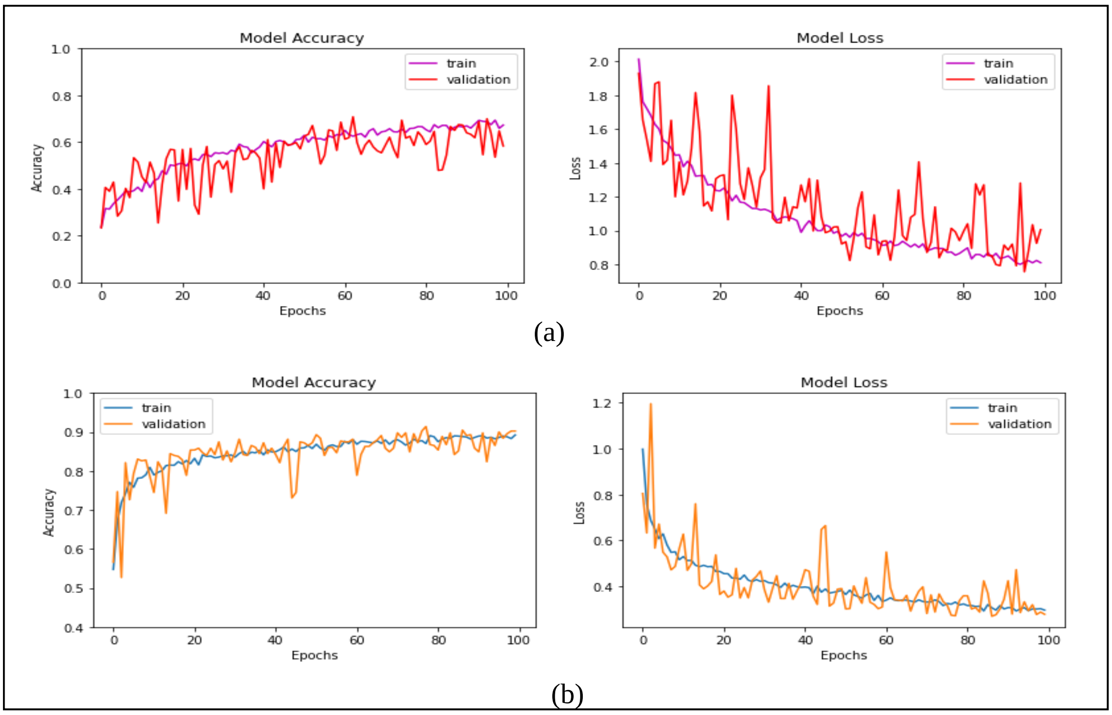

Figure 10. *ResNet-50 classification accuracy & loss function plots for (a) tomato and (b) potato*

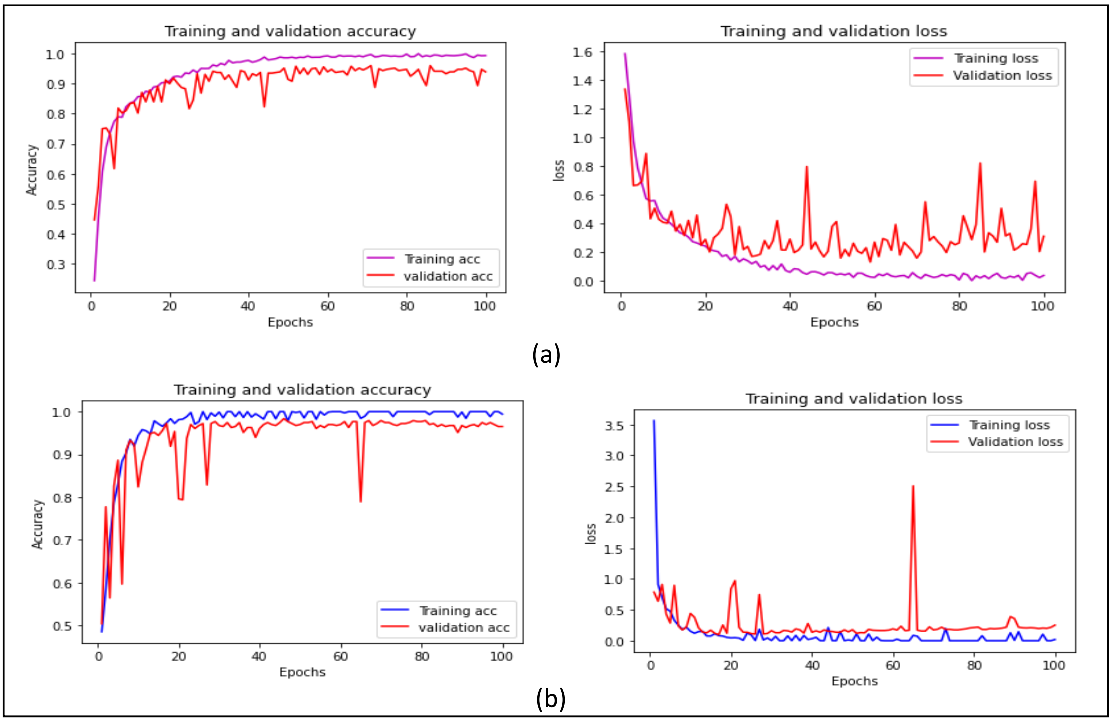

Figure 11. *Shallow-ConvNet (proposed model) classification accuracy & loss function plots for (a) tomato and (b) potato*

The suggested CNN architecture has accomplished the classification accuracy (validation) 96.04% and 98.38% with 100 epochs for tomato and potato leaf

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classification respectively (*Tables 7* and *8*) and average accuracy (validation) is 97.22% (*Table 9*), which is greater than existing CNN architectures like ResNet-50, VGG-16, and VGG-19, evaluated in parallel to the proposed model. A snapshot of average accuracies obtained with different CNN models run for 100 epochs is given in *Figure 12*.

Table 9. *Average training and validation accuracies of pre-trained CNNs and proposed model*

Average accuracy (%)	Epochs	CNN models			
		VGG-16	VGG-19	ResNet-50	Shallow-ConvNet
Training	100	99.87	100	79.3	100
Validation	100	93.55	92.96	81.13	97.22

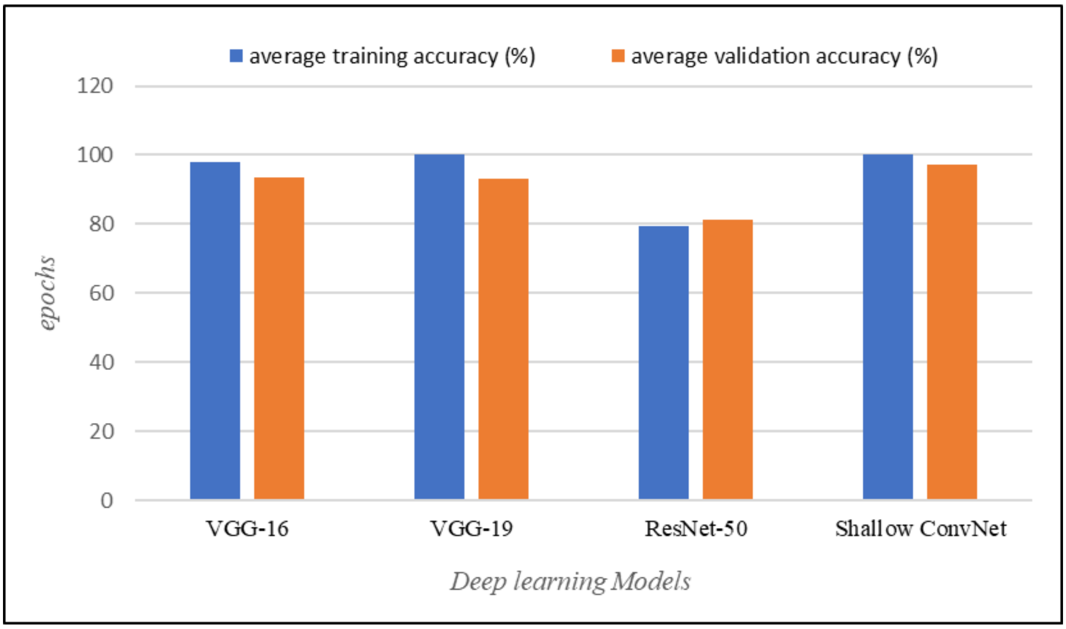

Figure 12. *Average classification accuracies (training & validation) with different CNN models*

Conclusion and future directions

Crops quality and output can be affected by a range of diseases brought on by fungus, bacteria, or imbalanced environmental circumstances. Therefore, the use of cutting-edge phytosanitary treatments is essential for the quick identification of crop diseases and the prompt implementation of preventative measures. This study's authors have suggested and experimented a light-weight CNN model, *Shallow-ConvNet* for crop leaf disease classification which has a very less number layers and parameters as compared to recent pre-trained CNN models. The simplified structure of CNN model having very less layers and parameters reduces the computing resources and time needed the model learning. The proposed model is empirically assessed for performance analysis using the hybrid dataset, which consists of 7166 samples of tomato and potato leaves, against the existing CNN architectures (ResNet-50, VGG-16, and VGG-19) for

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DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

100 epochs. The suggested Shallow-ConvNet has obtained an average classification accuracy of 97.22%, which is substantially better than the accuracies obtained by recent existing CNN models (ResNet-50 (81.13%), VGG-16 (93.5%), and VGG-19 (92.16%) that were evaluated concurrently with the proposed model. The experimental findings (*Tables 7*, *8*, and *9*), make it abundantly evident that the suggested model beats the most current pre-trained CNN models in accuracy and take less time to train. As a future recommendation, the suggested architecture could be trained and tested on a pure real field dataset images with complex backgrounds for a multi crop disease classification in conjunction with image pre-processing techniques to improve the quality of input real field images. In addition, the suggested model does not consider pathogen type or severity level detection, only the diagnosis of plant leaf disease. So, the study may be expanded in the future to include pathogen and severity level detection too.

Acknowledgements. "This work was supported by the Department of Science and Technology (DST), Government of India, New Delhi, under the Interdisciplinary Cyber-Physical Systems (ICPS) Programme (Project Tilted "Application of Internet of Things (IoT) in Agriculture Sector," Reference No. T-319)".

Conflict of interests. The authors declare that they have no conflicts of interests.

REFERENCES

[1] Abbas, A., Jain, S., Gour, M., Vankudothu, S. (2021): Tomato plant disease detection using transfer learning with C-GAN synthetic images. – Computers and Electronics in Agriculture 187(June): 106279. https://doi.org/10.1016/j.compag.2021.106279.

[2] Agarwal, M., Singh, A., Arjaria, S., Sinha, A., Gupta, S. (2020): ToLeD: tomato leaf disease detection using convolution neural network. – Procedia Computer Science 167(2019): 293-301. https://doi.org/10.1016/j.procs.2020.03.225.

[3] Amara, J., Bouaziz, B., Algergawy, A. (2017): A Deep learning-based approach for banana leaf diseases classification. – Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI) 266: 79-88.

[4] Ashwinkumar, S., Rajagopal, S., Manimaran, V., Jegajothi, B. (2021): Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks. – Materials Today: Proceedings 51: 480-487. https://doi.org/10.1016/j.matpr.2021.05.584.

[5] Bhujel, A., Kim, N. E., Arulmozhi, E., Basak, J. K., Kim, H. T. (2022a): A lightweight attention-based convolutional neural networks for tomato leaf disease classification. – Agriculture (Switzerland) 12(2): 1-18.

[6] Bhujel, A., Kim, N.-E., Arulmozhi, E., Basak, J. K., Kim, H.-T. (2022b): A lightweight attention-based convolutional neural networks for tomato leaf disease classification. – Agriculture 12(2): 228. https://www.mdpi.com/2077-0472/12/2/228 [8 February 2023].

[7] Choi, D., Shallue, C. J., Nado, Z., Lee, J., Maddison, C. J., Dahl, G. E. (2019): On empirical comparisons of optimizers for deep learning. – http://arxiv.org/abs/1910.05446.

[8] Chouhan, S. S., Singh, U. P., Jain, S. (2020): Applications of computer vision in plant pathology: a survey. – Archives of Computational Methods in Engineering 27(2): 611-632. https://doi.org/10.1007/s11831-019-09324-0.

[9] Chowdhury, M. E. H., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., Al-Emadi, N., Reaz, M. B. I., Islam, M. T., Ali, S. H. M. (2021): Automatic and reliable leaf disease detection using deep learning techniques. – AgriEngineering 3(2): 294-312.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

[10] Elaraby, A., Hamdy, W., Alruwaili, M. (2022): Optimization of deep learning model for plant disease detection using particle swarm optimizer. – Computers, Materials and Continua 71(2): 4019-4031.
[11] Elfatimi, E., Eryigit, R., Elfatimi, L. (2022): Beans leaf diseases classification using MobileNet models. – IEEE Access 10: 9471-9482.
[12] Ferentinos, K. P. (2018): Deep learning models for plant disease detection and diagnosis. – Computers and Electronics in Agriculture 145: 311-318.
[13] Gadekallu, T. R., Rajput, D. S., Reddy, M. P. K., Lakshmanna, K., Bhattacharya, S., Singh, S., Jolfaei, A., Alazab, M. (2021): A novel PCA–Whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. – Journal of Real-Time Image Processing 18(4): 1383-1396. https://doi.org/10.1007/s11554-020-00987-8.
[14] Gao, J., Westergaard, J. C., Sundmark, E. H. R., Bagge, M., Liljeroth, E., Alexandersson, E. (2021): Automatic late blight lesion recognition and severity quantification based on field imagery of diverse potato genotypes by deep learning. – Knowledge-Based Systems 214: 106723. https://doi.org/10.1016/j.knosys.2020.106723.
[15] Gokulnath, B. V., Usha Devi, G. (2021): Identifying and classifying plant disease using resilient LF-CNN. – Ecological Informatics 63(February): 101283. https://doi.org/10.1016/j.ecoinf.2021.101283.
[16] Hassan, S. M., Jasinski, M., Leonowicz, Z., Jasinska, E., Maji, A. K. (2021a): Plant disease identification using shallow convolutional neural network. – Agronomy 11(12): 2388. https://www.mdpi.com/2073-4395/11/12/2388 [8 February 2023].
[17] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., Jasińska, E. (2021b): Identification of plant-leaf diseases using CNN and transfer-learning approach. – Electron. 10(12). DOI: 10.3390/Electronics101213.
[18] Hassanien, A. E., Gaber, T., Mokhtar, U., Hefny, H. (2017): An improved moth flame optimization algorithm based on rough sets for tomato diseases detection. – Computers and Electronics in Agriculture 136: 86-96. http://dx.doi.org/10.1016/j.compag.2017.02.026.
[19] Huang, S., Liu, W., Qi, F., Yang, K. (2019): Development and validation of a deep learning algorithm for the recognition of plant disease. – Proceedings - 21st IEEE International Conference on High Performance Computing and Communications, 17th IEEE International Conference on Smart City and 5th IEEE International Conference on Data Science and Systems, HPCC/SmartCity/DSS 2019 1951-1957.
[20] Katoch, O. R. (2012): Perception of vegetable growers towards tomato production in Doda District of Jammu & Kashmir - India. – EXCEL International Journal of Multidisciplinary Management Studies2(11): 8834.
[21] Katoch, O. R., Oerke, E. C. (2012): Crop losses to pests. – Journal of Agricultural Science 2(1): 8834.
[22] Kaya, Y. and Gürsoy, E. (2023): A novel multi-head CNN design to identify plant diseases using the fusion of RGB images. – Ecological Informatics 75: 101998.
[23] Khan, M. A., Akram, T., Sharif, M., Awais, M., Javed, K., Ali, H., Saba, T. (2018): CCDF: automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features. – Computers and Electronics in Agriculture 155(September): 220-236. https://doi.org/10.1016/j.compag.2018.10.013.
[24] Kumar Sahu, S. and Pandey, M. (2023): An optimal hybrid multiclass SVM for plant leaf disease detection using spatial fuzzy C-Means Model. – Expert Systems with Applications 214: 118989.
[25] Lin, J., Chen, X., Pan, R., Cao, T., Cai, J., Chen, Y., Peng, X., Cernava, T., Zhang, X. (2022): GrapeNet: a lightweight convolutional neural network model for identification of grape leaf diseases. – Agriculture (Switzerland) 12(6).
[26] Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., Sun, Z. (2018): a recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2104_31933211

network. – Computers and Electronics in Agriculture 154(June): 18-24. https://doi.org/10.1016/j.compag.2018.08.048.
[27] Nwankpa, C., Ijomah, W., Gachagan, A., Marshall, S. (2018): Activation functions: comparison of trends in practice and research for deep learning. – http://arxiv.org/abs/1811.03378.
[28] Singh, A. K., Sreenivasu, S. V. N., Mahalaxmi, U. S. B. K., Sharma, H., Patil, D. D., Asenso, E. (2022): Hybrid feature-based disease detection in plant leaf using convolutional neural network, Bayesian optimized SVM, and random forest classifier. – Journal of Food Quality. https://doi.org/10.1155/2022/2845320.
[29] Sun, H., Xu, H., Liu, B., He, D., He, J., Zhang, H., Geng, N. (2021): MEAN-SSD: a novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks. – Computers and Electronics in Agriculture 189(November 2020): 106379. https://doi.org/10.1016/j.compag.2021.106379.
[30] Verma, S., Chug, A., Singh, A. P. (2020a): Exploring capsule networks for disease classification in plants. – Journal of Statistics and Management Systems 23(2): 307-315.
[31] Verma, S., Chug, A., Singh, A. P. (2020b): Application of convolutional neural networks for evaluation of disease severity in tomato plant. – Journal of Discrete Mathematical Sciences and Cryptography 23(1): 273-282.
[32] Wang, G., Sun, Y., Wang, J. (2017): Automatic image-based plant disease severity estimation using deep learning. – Computational Intelligence and Neuroscience. https://doi.org/10.1155/2017/2917536.
[33] Wspanialy, P. and Moussa, M. (2020): A detection and severity estimation system for generic diseases of tomato greenhouse plants. – Computers and Electronics in Agriculture 178(April): 105701. https://doi.org/10.1016/j.compag.2020.105701.
[34] Yong, L. Z., Khairunniza-Bejo, S., Jahari, M., Muharam, F. M. (2023): Automatic disease detection of basal stem rot using deep learning and hyperspectral imaging. – Agriculture (Switzerland) 13(1).
[35] Zhang, S., Wang, H., Huang, W., You, Z. (2018): Plant diseased leaf segmentation and recognition by fusion of Superpixel, K-means and PHOG. – Optik 157: 866-872. http://dx.doi.org/10.1016/j.ijleo.2017.11.190.
[36] Zhang, S., You, Z., Wu, X. (2019): Plant disease leaf image segmentation based on Superpixel clustering and EM algorithm. – Neural Computing and Applications 31(s2): 1225-1232.

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