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A Heuristic Approach to Ensemble-Based Deep Learning Models for Plant Disease Classification and Farming Decision Support

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Abstract

Leaf based plant diseases detection is one of the significant factors affecting crop yield and productivity. Most of the current techniques used for disease prediction are trained using observational records featuring numerous plant image parameters, with a higher frequency of diseased images compared to blight-free images. Hence, discriminating against the crucial insights from irrelevant and redundant images has been a crucial and challenging study. This research inspects the suitability of machine learning models in disease prediction focusing both specific and wide range of plant leaf images. Also, most classical methods are pretentious by various issues such as the format of image statistics, computation, and representation. To address this crucial setback in the present prediction methods, the proposed system develops a hybrid model utilizing stacked ensemble learning, which enhances the detection of plant disease attacks beyond what conventional learning methods. The proposed stacked ensemble-based disease prediction framework is designed to identify both misclassified and correctly classified images. This approach features a two-tier classification mechanism that involves a base learner (Level 0) and a meta learner (Level 1). It considers both image datasets and image features as inputs to facilitate the two-tier classification process. It also focuses on extracting internal features from the damaged leaves. The proposed model was trained with over 30,000 images at various levels. The experimental results revealed that the stacked ensemble learning technique outperformed with a prediction accuracy of 99.93%..

Keywords

Stacked ensemble learning, conventional learning, base learners, meta learners, inception, classification and accuracy.

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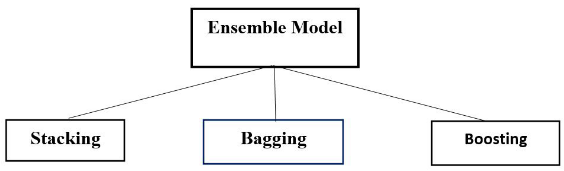
Introduction

Early detection of plant diseases focuses mainly on monitoring the well-being of the plant to prevent the spread of infections. (Li et al., 2021) outlined that the importance of diseases that appear on fruit trees have a great influence on agricultural production. In this research investigates the benefits of using ensemble-based machine learning in plant disease detection. Ensemble techniques are typically applied in three different ways, as illustrated in Figure 1. In this, bagging ensemble model is also known as the parallel ensemble and this computes the prediction result by averaging the responses of the N classifiers, where N is the total number of classifiers used in the system. A boosting model, often referred to as a sequential ensemble, achieves the desired result by adjusting the weights with each iteration. The boosting ensemble technique has potential to reduce the bias. Wherein, the stacking model trains multiple classifiers in parallel, and the result is obtained from the second-level classifier (Chen et al., 2023). Table 1 elucidates the merits and demerits of three existing ensembles techniques. Thus, after conducting a deep analysis the proposed framework is modelled using stacking ensemble approach, it is premeditated using four effective deep learning classifiers.



Source: compiled by the authors

Figure 1: Types of ensemble models.

Bagging	Boosting	Stacking
Parallel and popular ensemble method with prediction variance	Sequential ensemble with predictive data analysis	Multiple Classifiers are trained parallel
Results are obtained by averaging the responses of the N learners	On each iteration, update the model by weights until desired result is obtained	Results are obtained from the second level classifier
Reduce the variance	Reduce the bias	Increases the accuracy of classification model

Source: compiled by the authors

Table 1: Ensemble techniques.

Literature survey

In the study by Li et al. (2021), stacking ensemble learning is introduced as a method for diagnosing diseases in fruit-bearing trees. This approach combines various machine learning algorithms to improve predictive performance by leveraging multiple models. The diagnostic model was developed using a dataset comprising 10,000 pear images. To enhance performance, three types of ensemble learning classifiers and two types of deep learning classifiers were evaluated and tested. The stacking ensemble learning classifier achieved the highest accuracy, with 98.05% on the validation dataset and 97.34% on the test dataset, outperforming the other classifiers. Additionally, three lightweight Convolutional Neural Networks (CNNs) SEMobileNet, Mobile-DANet, and Mobile Net V2 were merged to create a new network named Es-MbNet for identifying types of plant diseases.

The model training incorporated transfer learning and a two-step training approach, where the first step focused on initializing the network weights. In the second step, pre-trained models utilized the weights from the initial phase to make predictions on the target dataset, effectively optimizing the model's parameters. This method, proposed by Chen et al. (2023), achieved an impressive average accuracy of 99.37% on a local dataset. To assess the model's robustness, it was also evaluated using the open-source Plant Village dataset, yielding an average accuracy of 99.61%. The objective of this study is to classify plant diseases using images captured directly in the field. To enhance predictability, ensemble learning techniques were explored to construct a robust network aimed at identifying four distinct pear leaf diseases. Various convolutional neural network architectures including EfficientNetB0, InceptionV3, MobileNetV2, and VGG19 were compared and combined. This ensemble approach enhanced predictive performance through the implementation of a bagging strategy and weighted averaging (Fenu and Malloci, 2023). Quantifiable experiments were performed to assess the model using the DiaMOS plant dataset, followed by the application of data augmentation to enhance the model's generalization capabilities. The results are evaluated with a range of metrics, including accuracy, recall, precision, and f1-score. The results showed that the proposed ensemble convolutional neural network outperformed the single convolutional neural network in classifying diseases in real-field conditions.

Typically, challenges such as variations in brightness, similarities in diseases, intricate backgrounds, and the presence of multiple leaves in images pose difficulties for machine learning and deep learning algorithms in making accurate predictions. Leaf diseases significantly impact the quality of agricultural products, making it essential for farmers to quickly halt their spread. This study introduces a stacking ensemble of a lightweight learning CNN framework aimed at improving the recognition accuracy of images depicting plant leaf diseases. (Enkvetchakul and Surinta, 2022), proposed four lightweight CNN architectures InceptionResNetV2, NASNet-Mobile, MobileNetV2, and Efficient Net B1 to develop an effective CNN model for plant leaf disease detection. The experimental findings indicated that EfficientNetB1 outperformed the other CNN models. The analysis utilized classifiers including logistic regression, support vector machine, K-nearest neighbors, random forest, and long short-term memory network. Among these, the random forest method proved to be the most suitable model. Ocular diseases tend to develop slowly, and since they can be severe and untreatable, regular check-ups are necessary to catch them early, though this can increase the workload. Consequently, an automated system powered by deep learning could facilitate early detection of these diseases.

Agarwal et al. (2022), identified healthy and unhealthy plants, using the CNN model. The study sheds light on how well deep learning methods work for automatically identifying plant diseases, which has a big influence on farming operations. In Kaur et al. (2022), deep learning and object detection techniques are presented in this paper to detect or characterize infected areas in tomato leaf diseases. This research work determines and measures the level of infection in tomato leaves.

Gautam et al. (2024) presented a novel approach for mango leaf disease classification and detection. The novel approach, ESDNN, is an ensemble-stacked deep neural network used to increase the precision of illness detection and classification in mango leaves. It is composed of many deep neural networks. The research indicates that the ESDNN model is a useful tool for early diagnosis and management methods since it can reliably identify and classify several mango leaf diseases.

Ranjan and Kumar (2023) highlighted the fruit Fly Optimization Algorithm (FOA) and described their proposed ideas, and distinctions. Sunil et al., (2022), presented a systematic review on Fruit Fly Optimization Algorithm and Its Applications. The authors conduct a thorough literature analysis to provide an overview of the main ideas, variations, and uses of the FOA across a range of industries. The goal of the study is to shed light on the FOA's adaptability and efficacy as an optimization method. Ayan (2024) used an approach-based genetic algorithm-based hyperparameter optimization to optimize CNN hyperparameters for crop pest classification. Using evolutionary algorithms to optimize critical hyperparameters, it is reliable and classifies agricultural pests.

Tiwari et al. (2020) presented a solution for the detection of multiple ocular diseases from fundus images. Based on the combined dataset of ocular disease images, the faster ensemble model had an accuracy of 87%, while the ensemble model had an accuracy of 88%. This research work has adopted the stacked ensemble deep learning model to resolve the problem of automatic identification of mango-leaf diseases. In the proposed approach, initially, the images are segmented for the region of interest and input to a stack of various deep neural networks. The outcome of the deep neural network is aggregated with a machine learning model to identify leaf diseases.

One of the previous works by Patil et al. (2024) on ensemble of Deep Convolutional Neural Networks (DCNNs) for crop classification using aerial imagery outlined the aerial photos preprocessing method and demonstrated on raining the model with a distinct set of filter sizes and scales. The classification accuracy significantly increased by combining the outputs from these DCNNs using an ensemble technique.

Kalita et al. (2023) outlined an enhanced deep CNN approach in the identification of grape leaf diseases. Preprocessing grape leaf photos, training CNNs on a tagged image dataset, and assessing the model's accuracy in categorizing various grape leaf illnesses are probably the steps in the methodology. To support early disease detection and control in grape production, it is intended to increase the precision and dependability of grape leaf disease identification.

Liu et al. (2020) discussed in detail about decision trees, support vector machines, and neural networks are combined to predict diseases. Uddin et al. (2019) used a combination of deep learning networks and K-means segmentation approaches to predict and categorize potato leaf illnesses.

Nishad et al., 2022) described the application of Vision Transformer (ViT) for disease classification in tomato leaves. ViT is a transformer-based model well-known for its performance in image classification tasks. Pre-processed photos of tomato leaves are fed into several ViT models for training and assessment. (Saleem et al., 2020), presented a deep learning meta-architecture approach for image-based plant disease identification. Cutting-edge deep learning methods to increase plant disease identification efficiency and accuracy. Improve the identification system's performance, probably entails creating meta-architecture that integrate several deep learning models or include unique architectural components. The method consists of labelling datasets, preprocessing plant photos, training deep learning models on them, and assessing how well the algorithms identify different plant illnesses. Iniyan and Jebakumar (2022) proposed a multi-layer stacked ensemble learning technique increase the accuracy of yield predictions for soybean crops.

Kale et al. (2021) proposed deep learning models to detect the factors of mango crop production and quality. Yousuf and Khan (2021) describes an ensemble model based on Random Forest and K-Nearest Neighbor (KNN) for the detection of plant diseases from the leaves. The proposed ensemble has detected the diseases using four phases. In the first phase, the segmentation of leaf images is done by K-Means Clustering. The second phase is to feature extraction process. In this phase, the GLCM approach is adopted. The third phase consists of a feature selection approach. For that, the Random Forest method is applied, and finally the classification of plant disease by KNN and SVM. The proposed approach outperformed the SVM method. (Sutaji and Yıldız. 2022), presented a compact and effective model is proposed to predict the illness by combining the Xception and MobileNetV2 models.

Nagaraju et al. (2022) dealt wit an image augmentation method for identifying and categorizing diseases in maize crops. The technique creates augmented photos that boost the quality and diversity of the dataset used to train machine-learning models, to increase the accuracy of disease recognition. Al-gaashani et al. (2022) used pre-trained models and feature extraction techniques to detect the diseases of tomato leaves. To improve classification accuracy, the method makes use of feature concatenation and transfer learning approaches. Through feature concatenation and information transfer from pre-trained models, the strategy enhances the robustness of disease classification in tomato leaves. Chy et al. (2023) adopted an optimized model to detect corn diseases. The corn diseases are Corn common leaf rust, Corn Common rust, Corn Northern Leaf Blight, and healthy leaves. The obtained overall accuracy is 97.6%, and each category accuracy was greater than 95%.

Most of the exiting works have utilized an independent classifier for decision-making. While, in the proposed work, two-level classification is proposed. The proposed system has implemented the classification task as two level, at level -1 base learner with InceptionV3, Xception, and Densenet201. (Hasan et al., 2022) outlined the various deep learning models. The CNN model is used for the Meta classifier generation (Mishra et al., 2020). Generally, in stacking, if the base classifiers are machine learning, the Meta classifier is also machine learning. Since the proposed method adopted three advanced deep learning models as the base learners, the Meta classifier must also be a deep learning model (Panchal et al., 2023). Thus, the proposed method uses CNN as the meta-learner.

Materials and methods

The benchmarked Kaggle dataset Village Plant is used to experiment with the proposed method. This dataset contains potato, corn, grape, and apple plants have healthy and diseased leaf images. Table 2 provides leaf disease details, and the total number of images present in the dataset.

Leaf disease description

The early blight disease of potatoes is caused by the fungus Alternaria solani. This kind of disease generally appears on the leaflet of a potato after 3 to 4 weeks of finding symptoms like brown spots, dark spots, and angular spots. Climatic conditions or soil conditions tend to stimulate diseases. Black rot diseases are causing severe losses in apple and grape plants due to the fungus causal agent. It produces dark brown discoloration and decay, mainly in the leafy part of the plant. It is a common disease caused by berry rot and leaf spot. Apple scab is caused by fungus in the apple leaves with velvety olive-green spots with unclear margins. Later, the lesions enlarge and become darker, with more distinct margins. Heavily infected leaves become dizzy and drop early in the summer season. The northern leaf blight is very easy to find along field edges, likely due to increased air movement for spore dispersal. It lacks the freckles in the lesions and bacterial streaming. Symptoms may include a detectable change in color, shape, or function of the plant as it responds to the pathogen. Leaf wilting is a typical symptom of verticillium wilt, caused by fungal plant pathogens.

S.no	Plant type	Diseases	Number of images	Sample Image
1	Potato	Early_blight	1002	
		Late_blight	1000	
		Healthy	152	

Source: compiled by the authors based on the dataset

Table 2: Disease details and the total number of images present in the dataset. (To be continued).

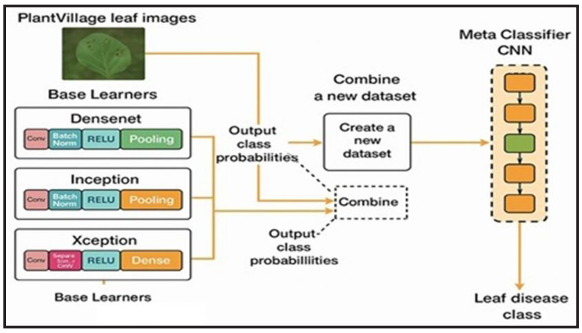
S.no	Plant type	Diseases	Number of images	Sample Image
2	Corn	Northern_Leaf_Blight	985	
		Cercospora_leaf_spot Gray_leaf_spot	513	
		Common_rust_	1192	
		Healthy	1162	
3	Grape	Black_rot	1180	
		Esca_ (Black_Measles)	1383	
		Leaf_blight_ (Isariopsis_Leaf_Spot)	1076	
		Healthy	423	
4	Apple	Apple_Apple_scab	630	
		Cedar_apple_rust	275	
		Black_rot	621	
		Healthy	1645	

Source: compiled by the authors based on the dataset

Table 2: Disease details and the total number of images present in the dataset. (Continuation).

System architecture

Figure 2 depicts the system architecture of the proposed system. The dataset contains healthy and diseased potatoes, corn, grape, and apple images. In the pre-processing step, the images are resized from 256x256x3 to 76x76x3. Image resizing is an essential part of handling the image data to make efficient use of the memory. The pre-processing steps include fixing the image resize by checking the lower values of the original image size. The proposed approach reduces the image ratio from 256, and 256, and 3 to 76, 76, and 3. This pre-processed data is then fed to the base learners twice, once with individual plants and once with combined plants, for the leaf image disease classification. In the first case, the leaf images of potatoes, corn, apples, and grapes are input individually. The execution time, accuracy, recall, and precision are calculated separately. In the second step, all the plant leaf images are combined into a single dataset and then fed as input for the model. The execution time and the performance metrics are computed for both, and the outputs are analyzed in the experimental section. The system architecture for both single plant and combined leaf image disease classification is similar, except for the input and output layers of deep learning models. Various modules are designed for single-plant and combined-plant leaf image classification using deep convolutional neural networks. The modules for pre-processing data and apply various classifiers and deep convolutional neural networks are as follows

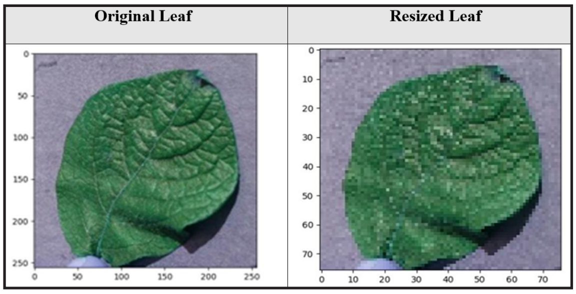


Source: compiled by the authors

Figure 2: Proposed stacked ensemble system architecture.

Resizing image

Image resizing is a process of scaling down or scaling up the dimensions of the images concerning maintaining the aspect ratio. When the image resizes is less than the aspect ratio, the image content cannot be preserved. But still, the image content is preserved without any loss (Iqbal and Talukder, 2020). The processing of original image data may consume more memory than predicting the final output. Thus, the proposed system applied various values to the height and width of the image to get the desired range. When the images were resized to 128x128x3, the system was unable to generate the array for all the images due to insufficient memory in the Kaggle as well as the local machine with the configuration of 64GB RAM. So, the proposed system resized the images gradually from 256, 128, 100, 84, and 76. Apart from 76X76X3, for the other above-mentioned resized images, the Numpy array could not be generated due to a lack of memory. This pixel reduction has two advantages. First, the training and testing time of the DL model will be reduced. If the number of pixels is high in the input image, the design complexity of the neural network model will also be increased. Figure 3 displays the original image 256, 256, and 3 and resizes that image into 76, 76, and 3.

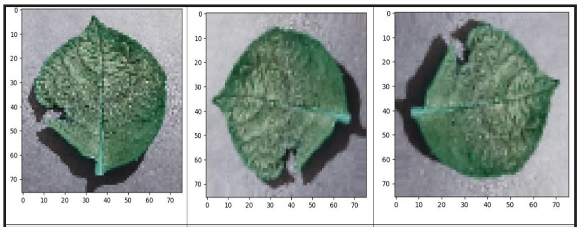


Source: compiled by the authors based on the dataset images

Figure 3: Potato plant leaf image resize.

Image data augmentation

Data augmentation generates new samples from the existing data. It is technically arranged and modified with some small changes to the dataset to assess the new training data by increasing the number of training sets. This training set ability is increased to generalize the variability and decrease the overfitting available in the data. Data augmentation improves the accuracy of the deep learning techniques and minimizes the data scarcity for the deep learning model. The techniques included in the data augmentation are flipping the image, resizing, cropping, and rotating the image. The data augmentation provides better performance by generating more samples. More samples are very useful to train the system so that the model can recognize more insights into the features of the input image. The proposed system thus generates two more samples of every leaf image by rotating the image to 90 degrees. Figure 4 shows the sample of potato leaf image augmentation.



(a) Original Leaf | (b) Augmented Leaf-1 | (c) Augmented Leaf-2

Source: compiled by the authors based on the dataset images

Figure 4: Potato plant leaf image data augmentation. (a) original image (b), original image is rotated into 90°, (c) rotated image is again rotated into 90°.

Base classifier (Level-0-Classifier)

The proposed stacked ensemble model adopted three deep learning models, namely Xception, Inception, and Densenet201 deep neural networks, as the base learners. The base learners create a new dataset that is inputted into the meta-classifier. The proposed model is also verified with combined-plant leaves (potato, corn, apple, and grape) and trained to recognize inter-plant leaf disease detection (Xie et al., 2020). The inter-plant leaf disease detection result analysis is explained in the experimental result section.

Meta classifier

The proposed method uses CNN as a meta-classifier. The input for the Meta classifier is a two-dimensional array, which consists of each classifier's predicted probability. The calculated probability value (0 to 1) for each disease in a leaf image. For possible 'n' diseases on a leaf, the classifier produces different predicted probability values based on the features recognized in the leaf (Vishnoi et al, 2022). If the leaf has a particular disease, then the classifier predicts. The probability value of that specific disease is higher than that of other diseases. The proposed method's performance on image classification is verified by adopting three different algorithms as metaclassifiers.

Proposed system algorithm

Step 1: Select the plant folder from plant village data source.

Step 2: Load the selected plant normal and diseases images in a directory D.

Step 3: Plant leaf image dataset

$D = \{D1, D2, D3, \ldots Dn\}$, where $D1, D2, D3, \ldots$ are plant image directories.

Step 4: Map the directory names as leaf disease names to generate labelled data.

Step 5: Split the selected plant images into training and testing set $DT = \{DT1, DT2, DT3, \ldots DTn\}$ $and\ DS = \{DS1, DS2, DS3, \ldots DSn\}$.

Step 6: Set rotation range = 90 of data augmentation to each $DT1, DT2, DT, \ldots$ in DT to double the training set.

Step 6: ***for each*** $DT1$ to DTn

for each image $(i1, i2, i3, \ldots, im)$, where m is the total number of images in the directory DTi

a. $ri_x \leftarrow_{\text{Resize}} image\ (i_x)$ into 76X76 pixel, where $x \rightarrow 1, 2, 3 \ldots m$

b. $ri_x\ {}_{\text{Convert}} \rightarrow narray$ [76, 76, 3]

c. $Nri_x \leftarrow ri_x/255[0,1]$

d. X_train$\leftarrow_{append}\ Nri_x$

e. Y_train $\leftarrow_{append}\ DTi$

end for

end for

Step 7: ***for each*** $DS1$ to DSn

for each image $(i1, i2, i3, \ldots, im)$, where m is the total number of images in the directory DSi

a. $ti_x \leftarrow_{\text{Resize}} image\ (i_x)$ into 76X76 pixel, where $x \rightarrow 1, 2, 3 \ldots m$

a. $ti_x\ {}_{\text{Convert}} \rightarrow narray$ [76, 76, 3]

b. $Nsi_x \leftarrow_{append}\ ti_x/255[0,1]$

c. X_test$\leftarrow_{append}\ Nsi_x$

d. Y_test $\leftarrow_{append}\ DSi$

end for

end for

Step 8: ***for each*** l in narray(range (0, len(X_train)

for each i in ***n***, where ***n*** is the total number of level-0-classifiers

for each j in disease (***d***), where ***d*** is the total number of diseases $\{(p_{i1l}, p_{i2l}, p_{i3l} \cdots, p_{ijl})\}$ predicted probabilities of ***j*** on the leaf array (***l***)

end for

end for

Generate predicted probability ***row set*** for the leaf l to generate the new input dataset (D') for the Meta classifier

$\{(p_{11l}, p_{12l}, p_{13l} \cdots, p_{1jl}),$
$(p_{21l}, p_{22l}, p_{23l} \cdots, p_{2jl}), \ldots,$
$|(p_{n1l}, p_{n2l}, p_{n3l} \cdots, p_{njl}), y_d\ \}$

end for

Step 9: ***for each*** row i_1 from the newly generated dataset (D')

Input i_1 to train the Meta Classifier ***for each*** output category $y_k \in \{y_1, y_2, y_3, \dots y_n\}$,

Calculate probability $p\left(\frac{n}{i_1}\right) = \frac{\exp(i_1 n)}{\sum_{j=1}^{n} \exp(i_1 n)}$ is calculated for the image i_1

Classify row $i_1 \leftarrow y_k \in \{y_1, y_2, y_3, \dots y_n\}$

Results and discussion

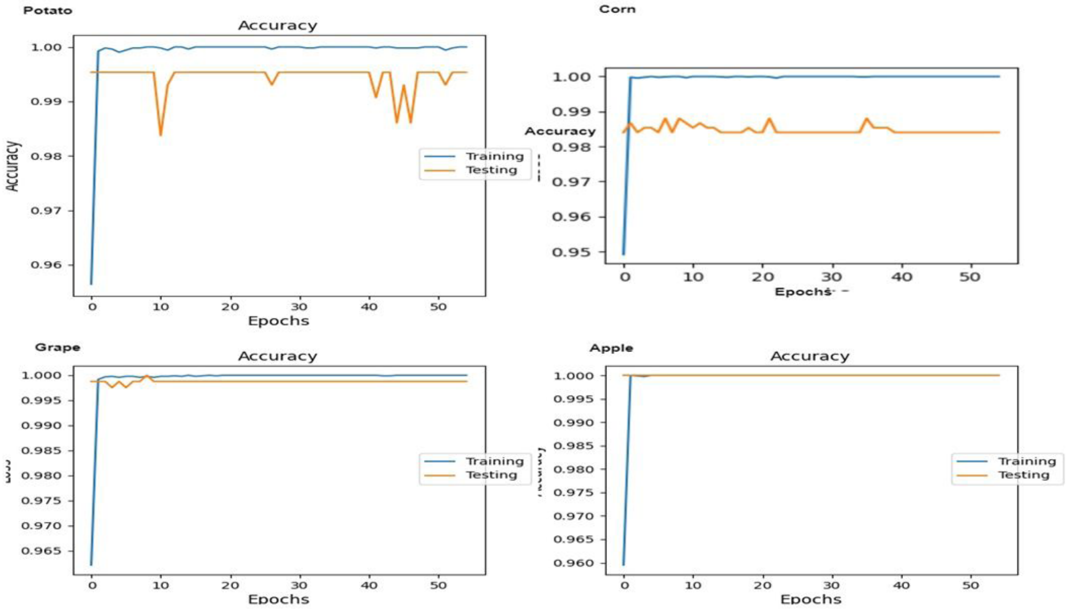
The proposed stacking ensemble system was trained and tested using the plant village dataset. The dataset covers samples of potato, corn, apple, and grape healthy and diseased leaf images. The model's performance outcomes as shown in Table 3 have reported significant improvement than the other classical approaches. The proposed model could predict diseases accurately. Model accuracy, precision, recall, and F1-score are estimates as per the equations 1, 2, 3, and 4 are applied to calculate (Wang et al., 2021). The classification accuracy lag in apple and potato leaf images was due to insufficient number of samples. Also, in sufficient datasets may report model under fitting and hence data sets play a vital role in data driven decision support systems. Also, the proposed stacking approach accuracy and loss results are shown in Figure 5 and Figure 6. In the testing phase of the proposed system, the misclassification is 0 for the apple. For the corn plants, the number of misclassifications is 12, the potato misclassification is 2 and the grape plants misclassification is 1.

The accuracy of the apple leaf images is significantly higher when compared to standalone machine learning and deep learning methods like VGG16 and random forest. The hybrid model's accuracy is lower than that of the proposed method for apple leaf images. For corn leaf images, deep learning models, including InceptionV2, ResNet50, and CNN, as well as machine learning algorithms, show lower accuracy than the proposed method. Likewise, the accuracy for grape and potato images surpasses that of the machine learning models. The proposed system was also evaluated using a unified dataset comprising all plant leaf images, referred to as combined plants. Table 4 presents the precision, recall, and F1 score results obtained for the combined plants through the proposed method. Analyzing the results for combined plants versus individual plants reveals that the performance metrics for combined potato plants are superior to those of individual potato plants. In contrast, the performance metrics for combined grape and corn plants are slightly lower (in fractional values) than those for the individual plants. However, the differences in performance results between combined and individual plants are minimal, owing to the classifiers utilized in level 0 classification.

Plant	Plant Disease / Evaluation Metrics	Precision	Recall	F1-score
Apple	Apple__Apple scab	1	1	1
	Apple___Black_rot	1	1	1
	Apple___Cedar_apple_rust	1	1	1
	Apple___healthy	1	1	1
Corn	Corn_Cercospora_leaf_spot Gray_leaf_spot	0.97	0.92	0.95
	Corn_Common_rust	1	1	1
	Corn_Northern_Leaf_Blight	0.96	0.98	0.97
	Corn_healthy	1	1	1
Grapes	Grape_Black_rot	1	1	1
	Grape_Esca_(Black_Measles)	1	1	1
	Grape_Leaf_blight	1	1	1
	Grape_healthy	1	1	1
Potato	Potato_Early_blight	1	1	1
	Potato_Late_blight	0.99	1	0.99
	Potato healthy	1	0.94	0.97

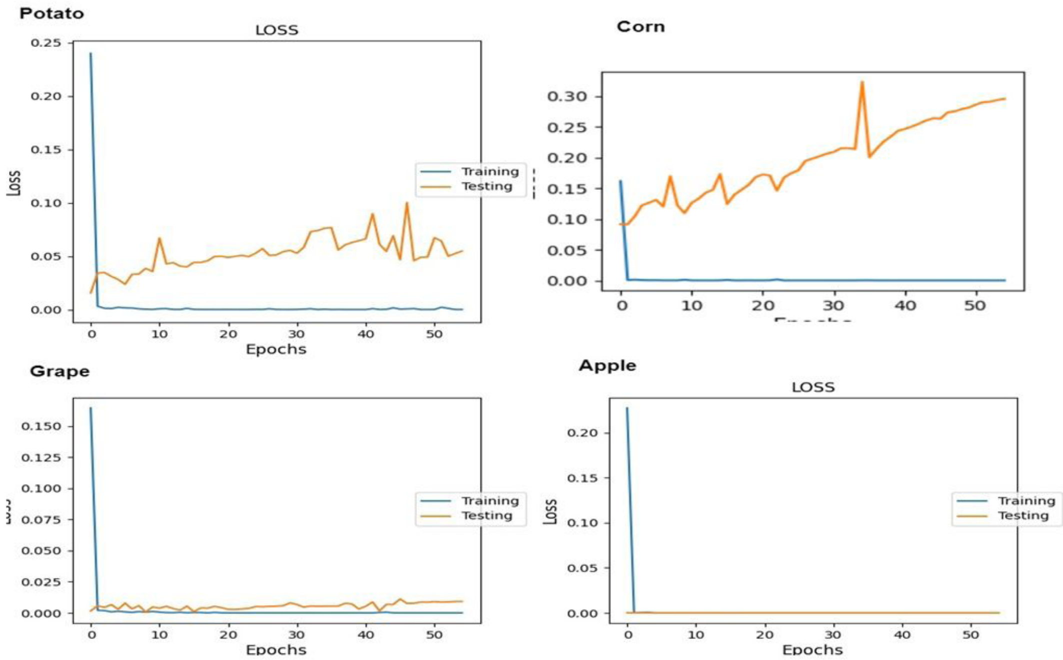
Source: compiled by the authors based on the dataset images

Table 3: Performance metrics results of individual plants.



Source: Own elaboration based on the model output

Figure 5: Accuracy results of a) potato b) corn c) grape d) apple individual plants leaves disease classification.



Source: Own elaboration based on the model output

Figure 6: Loss results of a) potato b) corn c) grape d) apple combined plants leaves disease classification.

Plant	Plant Disease / Evaluation Metrics	Precision	Recall	F1-score
Apple	Apple___Black_rot	1.00	1.00	1.00
	Apple___Cedar_apple_rust	1.00	1.00	1.00
	Apple___healthy	1.00	1.00	1.00
Corn	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.95	0.92	0.94
	Corn_(maize)___Common_rust	1.00	1.00	1.00
	Corn_(maize)___Northern_Leaf_Blight	0.96	0.96	0.96
	Corn_(maize)	0.99	1.00	0.99
Grape	Grape-Black_	1.00	1.00	1.00
	Grape___Esca_(Black_Measles	1.00	1.00	1.00
	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00
	Grape___healthy	0.99	1.00	0.99
Potato	Potato___Early_	1.00	1.00	1.00
	Potato___Late_blight	1.00	1.00	1.00
	Potato___healthy	1.00	1.00	1.00

Source: compiled by the authors based on the dataset images

Table 4: Performance metrics results of disease detection in apple, corn, grape & potato.

The total number of misclassifications in the combined plant dataset is low, with just 20 leaf images misidentified by the proposed method. The suggested stacked learning approach shows improved performance even when the dataset's size is increased two or threefold compared to the individual plant datasets. Consequently, the base classifiers in this design are sufficiently robust to assist the meta-learner in making precise predictions about leaf image diseases. Regarding runtime for the initial epoch, the processing times are as follows: apple takes 3 seconds and 7 milliseconds, grape requires 4 seconds and 6 milliseconds, potato also takes 3 seconds and 7 milliseconds, and corn needs 3 seconds and 6 milliseconds. For the combined plants, the first epoch lasts 6 seconds and 5 milliseconds.

Conclusion

This research work highlights the potential of stack ensembled model as a powerful and reliable framework for plant disease detection using leaf images. By effectively integrating multiple learning models in a two-tire classification system, also it overcomes the limitation of single-model techniques. The proposed stacked ensemble model has been designed using InceptionV3, Efficient Net, and DenseNet201 as base learners and CNN as its meta-learner. The predicted probability values from the base learners are compiled into a new dataset for the meta-model to produce the final prediction. This system was tested with two sets of image inputs. The first set included images of leaves from four distinct plants: potato, corn, grape, and apple, which were processed individually to compute performance metrics. In the second scenario, all the previously stated images were combined into a single input set to evaluate performance. In both instances, the experimental results demonstrated high performance, with minimal deviation between the two cases. It is principally attributed using three cutting-edge neural architectures that yield accurate probability predictions. The experimental findings further demonstrated that the proposed system outperforms existing methods. Its ability to accurately differentiate between healthy and diseased leaves, even in complex and diverse datasets, demonstrates its robustness and adaptability. The remarkable prediction accuracy of 99.9% highlights the efficiency of this hybrid model in capturing the subtle disease pattern and reducing misclassification rate. This research not only contributes to advancing intelligent agricultural advancements but also paves way for developing advanced scalable automated plant health monitoring systems to support sustainable farming practices.

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