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DeepCrop: Deep learning-based crop disease prediction with web application

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ABSTRACT

Agriculture plays a significant role in every nation's economy by producing crops. Plant disease identification is one of the most important aspects of maintaining an agriculturally developed nation. The timely and efficient detection of plant diseases is essential for a healthy and productive agricultural sector and to prevent wasting money and other resources. Various diseases that could affect a plant cause crop farmers to lose a substantial sum yearly. Deep learning can play a crucial role in helping farmers prevent crop failure by early disease detection in plant leaves. In the experiment, we examined CNN, VGG-16, VGG-19 and ResNet-50 models on plant-village 10000 image dataset to detect crop infection and got the accuracy rate of 98.60%, 92.39%, 96.15%, and 98.98% for CNN, VGG-16, VGG-19 and ResNet-50 respectively. The study indicates that ResNet-50 outperforms the other models with an accuracy of 98.98%. So, the ResNet50 model was chosen to be developed into a smart web application for real-life crop disease prediction. The proposed web application aims to assist farmers in identifying diseases of plants by analyzing photos of the plant leaves. The proposed application uses the ResNet50 transfer learning model at its heart to distinguish healthy and infected leaves and classify the present disease type. The goal is to help farmers save resources and prevent economic loss by detecting plant diseases early and applying the appropriate treatment.

1. Introduction

Agriculture is recognized as the backbone of any country, and the agricultural revolution is occurring concurrently with the industrial revolution. Crops are critical to our survival [1]. Food insecurity, the biggest reason for crop diseases, is one of modern humanity's most serious global challenges. Plant diseases can have a significant negative influence on our lives in addition to posing a global danger to food security. So crop health is very important for the economy and food safety. Only the growth and leaf condition represent the health condition of any crop.

Hence, knowledge of various plant diseases will be provided by studying leaf picture symptoms [2]. A variety of diseases that can affect a vegetable plant, such as potato, tomato, or pepper, can cause a farmer to lose a lot of money yearly. Blight comes in two flavors: early blight and late blight. Early blight is brought on by a fungus, while a specific bacterium brings on late blight. Farmers can avoid waste and expense if they can identify these diseases early and treat them effectively. The world population is expected to exceed 9 billion within the quarter of a century. To meet the ever-rising demand for food, there must be a 70% increase in food production. Crop disease is a formidable problem in many countries, especially agrarian ones. Especially since potato is the most popular vegetable in the world, diseases that occur in potatoes are pretty alarming. Nevertheless, the diseases in peppers and tomatoes are of grave concern as well. With the eternal motto, prevention is better than cure in mind. Agricultural scientists have been experimenting with deep learning to prevent potato crop diseases. Due to the tremendous progress in computing, by extracting data from real-time picture

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processing, machine learning techniques have been proven to be promising.

The importance of deep learning is immense, not to mention its growing popularity. It contributes immensely by making people's daily lives more convenient and will continue to do so in the future [3–5]. The quality and yield of the crop, as well as the leaves, fruits, stems, and roots, are all impacted by plant disease. This results in a shortage of vegetable consumption around the globe. Crop diseases cause a 16% loss in crop yield annually. Smart farming uses deep learning extensively as it adapts novel algorithms, equipment, and methods in the field [6]. Machine learning solves challenging issues in agriculture, like extracting features, transformation, pattern recognition, and image classifications [7,8]. To detect crop infections and determine the type of disease, an attempt has been made in this research to develop a CNN-based approach. As a result, if we can develop a system to implement the result in real-time, the output of this study may lessen the loss of crop yields.

Due to limited access to agricultural specialists in rural areas, Bangladeshi and Indian farmers have traditionally relied on their own knowledge and experience to identify crop diseases. Sometimes the specialist can identify the disease which is often too time-consuming, labor-intensive, and expensive to be widely used in developing nations. Considerable research has been conducted to address these challenges by developing artificial intelligence (AI)based solutions. Leveraging machine learning or deep learning techniques can expedite the detection process, leading to a significant reduction in crop damage. For example, [9] proposed a CNNbased framework for leaf disease detection. This research achieved an accuracy of 98.023%. [10] designed and developed a 15-layers custom CNN architecture to find the leaf diseases. However, the accuracy of the system was only 93%. [11] proposed a framework that employed EfficientNetB0 and DenseNet121 to obtain the deep features from corn plants. On the test dataset, ResNet152, InceptionV3, EfficientNetB0, and DenseNet121 achieved a 98.56%, 98.37%, 96.26%, 97.91%, and 97.82% accuracy in classification, respectively. The author suggested a dense-optimized convolutional neural network (CNN) to categorize four different types of corn leaves from the PlanVillage dataset [12]. The trained CNN was able to successfully classify data with an accuracy of 98.06%. [13] proposed a potato leaf disease detection model. Several deep learning models including VGG-16, VGG-19 and InceptionV3 have been incorporated as feature extractors from the potato leaves. Then, the extracted features are fed to the common machine learning algorithms like SVM, Neural Networks, KNN, and Logistic Regression for the classification task. The proposal achieved an accuracy of 97.8% for VGG19 and logistic regression. [14] proposed a framework to classify sunflower leaf diseases with a particle swap optimization algorithm. This paper achieved an accuracy of 98.00% in detecting different types of diseases. From the above-related literature, most of these works used default and built-in deep learning models in detection rather than tuning them. Furthermore, the accuracy of these proposed solutions is not at a satisfactory level, indicating the need for further research and improvement. Besides, any suggestive application to provide preliminary treatment can reduce crop loss significantly. The goal of this proposal is to create a deep learning-based detection framework capable of producing highly accurate results and offering initial recommendations for farmers. We try to solve the following research questions regarding the development of a smart crop disease detection in the agriculture sector: *a)How to lessen the suffering caused by the world's leading avoidable diseases? b)What kinds of deep learning strategies have been applied to identify crop diseases? c)In the case of plant disease detection, can deep learning systems compete with human experts? d)*How to find an efficient way to identify crop diseases?

The contributions of this research can be divided into two folds. Initially, a framework for deep learning-based disease identification has been suggested. The framework utilized several deep-learning models, VGG-16, ResNet50 and VGG-19, to investigate the correct performance in detecting crop disease. Extensive experiments are used to test the framework with a publicly available dataset. This dataset includes approximately 10000 pictures of various vegetables, including tomatoes, peppers, and potatoes leaves. Eventually, when evaluating the proposal's effectiveness, several accuracy measures are considered, including average training loss, training accuracy, validation accuracy and prediction accuracy for testing experiments. Secondly, the study's results led to selecting the ResNet50 model to be transformed into an intelligent web application for real-world crop disease prediction. The suggested web application's goal is to aid farmers in identifying plant diseases by looking at photos of the affected plants' leaves. Identifying plant diseases at an early stage and thus, it can assist farmers in conserving resources and avoiding economic loss.

The main contributions of this proposal can be summarized as follows:

- We suggest a framework for detecting crop diseases using deep learning. Multiple deep-learning models, such as VGG-16, VGG-19, and ResNet-50, have been utilized to investigate the performance of the proposal.
- Extensive experiments on a real-world dataset are used to evaluate the proposal. According to the findings, ResNet50 has the highest accuracy of 98.98% compared to the other two models.
- Finally, we develop a web application by utilizing ResNet50. This application can take crop images as input, detect the disease, and provide the farmer with recommendations for preliminary treatment.

The remainder of the paper is organized as follows: Our discussion of pertinent crop disease detection literature in Section 2 will give your research background and context. In Sections 3 and 4, we present the framework of our proposal, which includes the methodology and design of your research. Section 5 describes the data gathered for the experiments and the experimental setup and outcomes, which will be used to support our findings and conclusions. Section 6 will present how the web application was built, including the programming languages and tools used, the user interface design, and the application's functionality. At last, we wrap up our study in Section 7 with recommendations for future work to enhance our research.

2. Related works

The literature on leaf disease detection using deep learning is reviewed in this part, along with other essential research. The usage of AI in healthcare [15] and the agriculture sector has increased significantly in recent years. AI has been used in imaging, especially in the medical [16,17] and agricultural fields.

Sanjiv Sannakki et al. [18] utilized artificial intelligence and image processing in their endeavor to make a diagnosis. Using an image processing approach, Monika Jhuria et al. [19] were able to grade the fruit and identify illnesses. To help categorize diseases, an artificial neural network has been employed. Kaiyi Wang et al. [20] developed a new strategy for identifying insect pests and plant illnesses using image processing and computer vision techniques. Studying the state of insect pests and vegetable diseases using images gathered by smartphones.

Researchers have proposed and examined various methods and models for detecting plant diseases using machinelearning approaches. [21] describes distinguishing between healthy and diseased or infected leaves using image processing and machine-learning strategies. Several diseases cause leaves to lose chlorophyll, which causes dark or black patches to appear on the surface. They can be found using machine learning techniques for classification, feature extraction, image preprocessing, and image segmentation. Features are extracted using the Grey Level Cooccurrence Matrix (GLCM). The Support Vector Machine is one of the machine learning methods for categorization (SVM). The Convolutional Neural Network (CNN) technique increased recognition accuracy when compared to the SVM method. Apple leaves have a 99% overall accuracy. The classification of the respective plants is found to be 97.71% accurate. [22] described a rice leaf disease detection technique based on machine learning. Three of the most prevalent diseases affecting rice plants were identified in this study: leaf table, bacterial leaf blight, and brown spot diseases. Clear images of damaged rice leaves against a white background served as the input. After pre-processing, the dataset was trained using machine learning techniques, including KNN (K-Nearest Neighbor), J48 (Decision Tree), Bayesian Network, and Logistic Regression. After 10-fold cross-validation, the decision tree technique achieved an accuracy of over 97% when used on the test dataset. [23]; in their study, the outliers in wheat leaf were emphasized. Even though algorithms can detect common wheat leaf diseases, they harm wheat productivity. Viruses, bacteria, fungi, insects, rust, and other diseases affect wheat. Wheat leaves can be infected with a wide range of diseases. Identifying wheat diseases using leaf scanning and data processing techniques has become popular and expensive, especially for helping farmers monitor vast planted areas. Using a machine learning approach, wheat leaf disease classification and detection are also covered in detail. Furthermore covered are the primary issues and challenges in identifying wheat leaf disease. In Ref. [24], using Deep Learning methods, a Convolutional Neural Network (CNN) architecture is suggested for plant leaf disease detection. Several observations were taken using various CNN hyperparameters, and it was found that the suggested architecture can accurately classify diseases up to 95.81%. [25] focused on supervised machine learning algorithms for maize plant disease diagnosis using photographs of the plant, such as K-Nearest Neighbor (KNN), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Support Vector Machine (SVM). The RF algorithm, when compared to the other classification methods, gets the best accuracy of 79.23%. To avoid new image diseases from spreading, farmers will use all of the above-trained models for timely identification and classification. Image processing methods are applied to identify plant leaf diseases in Ref. [26]. This project aims to use image analysis classification algorithms to recognize and categorize leaf diseases. The suggested organization has four sections. First is image preprocessing; second is leaf segmentation using K-means clustering to locate hazardous areas. (4) Feature extraction and (3) categorization of diseases To extract texture data, statistical Grey-Level Co-Occurrence Matrices (GLCM) features are used, and a Support Vector Machine is used for classification (SVM). A. Meunkaewjinda et al. [27] proposed a system for detecting fruit diseases. Grape leaf color segmentation, grape leaf disease segmentation, and disease analysis and classification comprise the proposed system's three aspects. A pre-processing module called the grape leaf color segmentation removes any extraneous background information. A self-organizing feature map and back-propagation neural networks were employed to discern grape leaf colors. The grape leaf pixel segments in the image are created using this information. Support vector machines are then utilized to categorize various grape leaf diseases. The algorithm can categorize a grape leaf image into three groups: scab infection, rust ailments, and no disease. The suggested technique yields encouraging results that can be used in any system to examine or inspect agricultural products. Another study aims to apply the SVM classification method to help identify and classify grape leaf diseases [28]. The proposed approach has an accuracy of 88.89% for detecting and classifying the tested ailment.

Machine learning's most remarkable advancement is deep learning. Deep learning is the study of how a computer program may learn by observing and making decisions based on that knowledge. Deep learning algorithms benefit computer vision, face detection, audio recognition and processing, and various other applications. [29] suggested using open-source algorithms, image segmentation, and clustering to detect tomato plant leaves to disease, creating a trustworthy, secure, and accurate system for identifying leaf disease with an emphasis on tomato plants. The research in Durmuş et al. [30] where diseases that have been recognized harm greenhouse or field-grown tomatoes. Deep learning was used to identify different diseases in tomato plant leaves. The project aimed to have the deep learning algorithms run in real-time on the robot. As a result, the robot can detect plant illnesses while traveling on the field or in the greenhouse, either manually or automatically. Two distinct deep learning network topologies, AlexNet and SqueezeNet, were tried. These deep-learning networks were trained and validated on the Nvidia Jetson TX1. Photos of tomato leaves from the PlantVillage database were used for the training. There are ten separate classes, all of which have healthy imagery. Images from the internet are also used to test trained networks. [31] suggested a deep learning-enabled breakthrough for camera-assisted disease diagnosis in tomatoes. This research created a unique approach to disease detection in tomato plants. Four sides of each tomato plant were photographed using a motor-controlled picture-taking box to detect and diagnose leaf diseases. The tomato variety under test was one called Diamante Max. Among the diseases detected by the approach were Phoma Blight, Leaf Miner, and Targeted Spot. The system used a convolutional neural network to assess whether tomato infections were present on the plants being watched. Whereas the Transfer Learning disease recognition model has an accuracy of 95.75%, the F-RCNN trained anomaly-based model has an accuracy of just 80%. The automatic picture-taking system was tested in the real world and found to be 91.67% accurate at spotting illnesses on tomato plant leaves.

Table 1
Related literature on plant disease using deep learning models.

Reference	Object	Total no. of images and classes used	DL frames	Accuracy (%)
[[32]]	Citrus leaf	609 images with 5 classifications	Inception-v3, VGG-19 and VGG-16	Highest accuracy for VGG16–89.5%
[[33]]	Apple leaf	2462 images with 6 classifications	DenseNet-121	93.71%
[[13]]	Potato leaf	2152 images with 3 classifications	VGG19	97.8%
[[29]]	Tomato leaf	736 images with 4 classifications	CNN based approach	98.12%
[[34]]	Tomato leaf	7500 images with 9 classifications	CNN based approach	91.2%
[[35]]	Paddy leaf	120 images with 2 classifications	DNN-CSA	96.96%
[[36]]	Citrus leaf	598 images with 4 classifications	Two-stage deep CNN model	94.37%

By reviewing all relevant studies, it was observed that many studies used machine learning models to detect leaf disease. However, there are some drawbacks to utilizing machine learning models, such as the need for hand-crafted features for feature extraction, which can take time and may not necessarily produce the best representation of the data. Again, when there are few training samples, traditional machine learning approaches are subject to overfitting, making it difficult to generalize to updated data. In addition, several studies [29,32,35,36] use a small database for their experiment. Small datasets are likely to lead a CNN-based architecture to overfit. As a result, the model would not reflect actual and trustworthy classification performance outside of the training datasets. Moreover, numerous studies have only used a single pre-trained technique [13,33] and trained their architectures with a maximum of 5 or 6 classes [32,33]. Most importantly, they did not provide web applications for predicting crop diseases in the real world that could help farmers save resources and avoid financial loss. To circumvent the constraints for the experiments in the proposed study, many pre-trained deeplearning models and a large dataset of plant diseases were used. Additionally, the proposed model was compatible with eight different leaf classification categories. Significantly, we also built a smart web application for predicting crop disease. The summary of the related works is shown in Table 1.

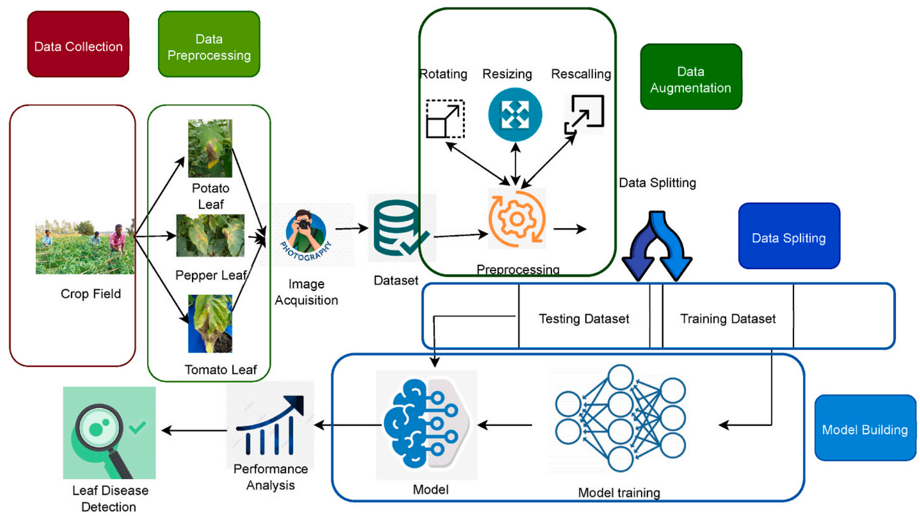


Fig. 1. Proposed work-flow diagram.

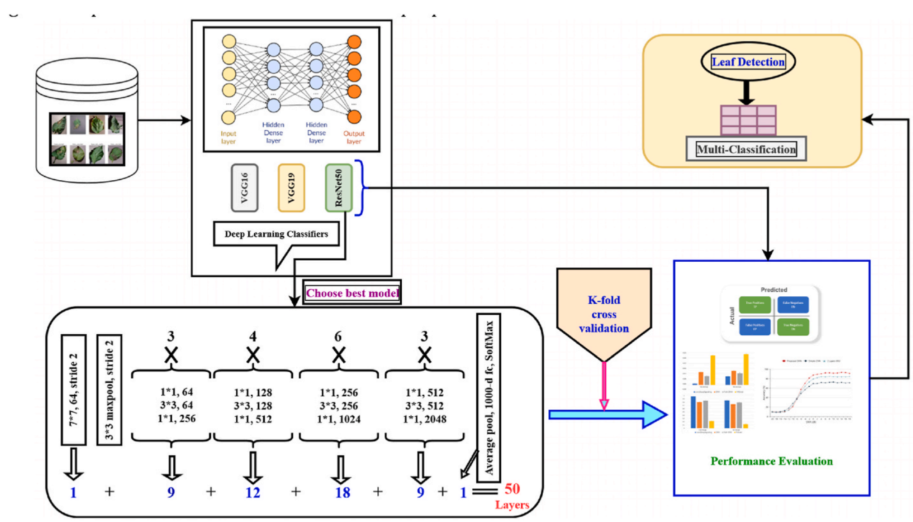


Fig. 2. Proposed model: three pre-trained deep learning models are used from then ResNet50 is finalized for selection; the layer-wise architecture details of ResNet50 are included.

3. Proposed methodology

The process of detecting diseases in plants is presented in Fig. 1. What follows, we describe each of the steps of the proposal:

3.1. Dataset

The proposal starts with collecting the input images representing different types of leaves like potatoes, tomatoes, and peppers. These raw images can be collected using a real-time camera or mobile. For our deployment, the deep learning model was trained using a publicly accessible dataset during the framework's testing and training phases.

3.2. Preprocessing

The raw images collected from the dataset might contain noises and it is essential to preprocess them before fitting them into the learning module. We apply rotation, resizing, and shearing to preprocess the image during the preprocessing phase.

3.3. Training and building the model

This step has two main phases. The TL models are trained using a training image dataset during the first phase.

During the later phase, the architecture is validated using test images reserved for performance evaluation.

3.4. Model construction

To build the predictive model, we apply the following steps:

- Collecting images from the dataset.
- Pre-process image data by resizing and rotating images.
- Creating convolute feature connect into Fully Connected Layers. Usually, it is flattened, converted to a one-dimensional (1D) array (or vector), and then joined to one or more completely connected layers.
- Finally, extract the features for different classes of the input.

Fig. 2 depicts the details architecture of the proposed model

3.5. Model evaluation

To evaluate the model, we apply the following steps:

- From an ideal dataset, 80% of photos are taken for training and 20% for testing.
- Validation data is used to check accuracy by applying the predict function and accurately extracting features.
- Images are taken for confirming detection once validation provides good results.
- Finally, characteristics are retrieved to determine whether or not the leaves are infected.

3.6. Performance evaluation

In this phase, we obtain the best model based on the performance of the extensive experiments. We used accuracy, precision, recall, f1score, training accuracy, training loss, validation accuracy, and validation loss. This will help to build the smart web application with deep learning guidance.

3.7. Deep learning models

We use the following deep TL methods in our framework.

- VGG-16: VGGNet-16 has 16 convolutional layers and a uniform design, considered one of the most extensively utilized structures for disease detection in image classification. The primary accomplishment of VGG-16 is demonstrating that, in some circumstances, growing network intensity can improve system performance [37]. Convolution, fully connected and pooling layers are three components of the VGG-16 transfer learning algorithm. The convolution layer (Conv) applies filters to pictures to extract information; its two most important properties are the kernel and stride size. The poling layer minimizes the network's spatial size and associated calculations.
- VGG-19: The CNN VGG-19 transfer learning model was first presented by Ref. [38]. It contains 3 dense layers, 16 convolutional layers, and 19 layers to categorize images into 1000 categories. The model is composed of 3 fully connected (FC) layers, 2 Conv 1 max pools, 4 Conv 1 max pool, 4 Conv 1 max pools, and 2 Conv 1 max pools. It is a very popular photo prediction model since each ConvNet uses a lot of 3×3 filters [7].
- ResNet50: The ResNet50 model is a subset of the ResNet family [39]; and 48 Convolutional layers, 1 MaxPool layer, and 1 Average Pool layer make up this structure. This ResNet model is well-liked for categorizing images. There are four main stages in the ResNet50 architecture. Three layers comprise the first convolution stage: a 1*1, 64 kernel, a 3*3,64 kernel, and finally a 1*1,256 kernel. In this stage, these three layers have replicated 3 times for a total of nine layers. Then, a kernel of 1*1,128 is seen, succeeded by a kernel of 3*3,128 and then a kernel of 1*1,512. For a total of 12 layers, this process was carried out four times. Following that, a 1*1,256 kernel is present, followed by two further kernels with 3*3,256 and 1*1,1024; this is continued six times, providing a total of 18 layers. Following that, a 1*1,512 kernel was constructed, then two further kernels of 3*3,512 and 1*1,2048. Three repetitions through this method gave us a total of nine layers. Fig. 2 shows the graphical representation of ResNet50 architecture.

3.8. Architectural comparison

Three common CNN transfer learning architectures are VGG-16, VGG-19, and ResNet50. The ImageNet dataset, which includes 1,000 different types of images, was used to train and improve the performance capabilities of each of these transfer learning algorithms. There are a number of factors that affect the accuracy and training error of any transfer learning model including the datasets type, the number of images and their size, the number of convolutions and pooling layers, the number of epochs, and the batch size of the simulation. Both VGG-16 and VGG-19 are very deep convolutional networks; the only distinction between them is the number of hidden layers. The VGG-16 is 16 layers deep, while the VGG-19 goes up to 19. Because of its deeper architecture, VGG19 frequently demonstrates a slightly improved accuracy. Although these two models can be used in image classification, they suffered from vanishing point problems. ResNet50 on the other hand, provides better accuracy due to the increasing number of layers. In general, the more levels there are in a hierarchy, the better it can represent data and make accurate classifications. Besides ResNet50 is easier to optimize and can handle the vanishing gradient problem, it provides better accuracy compared to the other two models. Table 2 demonstrates the architectural comparison of the three models.

Table 2
Architectural comparison of VGG-16, VGG-19 and ResNet50.

SL	Properties	VGG-16	VGG-19	ResNet-50
1	image	224*244*3	224*244*3	224*244*3
2	weight	imagenet	imagenet	imagenet
3	Model size	533 MB	574 MB	102 MB
4	Total layers	16	19	50
5	Convolution layer	13	16	48
6	Max pool	5	5	1
7	Activation function	Softmax	softmax	Softmax
8	Total parameters	138.3 million	143.7 million	25.6 million
Advantages/Limitation				
VGG-16		• It is painfully slow to train. • Weights are quite large. • Suffers from vanishing gradient.		
VGG-19		• Deeper than VGG-16. • Weights are quite large. • Suffers from the vanishing gradient.		
ResNet-50		• Faster than VGG-16 and VGG-19. • Low-power models parameterized to meet the resource constraints. • It can handle the vanishing gradient problem.		

Table 3
Confusion matrix.

	Actual positive	Actual negative
Predicted positive	TP	FP
Predicted negative	FN	TN

4. Experimental setup and implementation

4.1. Experimental setup and performance metrics

The experiments were performed on a PC with an 8 GB graphics card, 8 GB Memory, a Core i5 processor, 64-bit

Windows 10 running at 1.80 GHz, and the Python programming language.

Different deep learning models are explored and evaluated with respect to their performance based on the following metrics using the confusion matrix shown in Table 3:

Here TP represents True Positive, the model predicted the instance as disease affected leaf and the leaf was disease affected; TN represents True Negative-the model classified that the leaf is not affected and the leaf is healthy; FN represents False Negative-the model predicted the instance as a healthy leaf but actually it was affected; and FP represents False Negative-the model classified it as disease affected leaf but it was a healthy instance respectively. • **Accuracy:** The proportion of test cases for which a correct prediction was made can be expressed as follows:

Table 4
Experimental parameters setting.

Parameters	Values
Learning Rate	.001
Drop out	0.01
Optimizer	Adam
Shearing	−0.3 to +.3
Horizontal flipping	True
Rotating	−10 to +10
Zooming	0.5 to 1.5
Batch Size	32
Validation split	0.2

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

- **Precision:** The ratio of correctly predicted disease-affected leaves to all positively predicted leaves by the model is known as precision and can be defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- **Recall:** recall is defined as the percentage of correctly predicted disease-affected leaves relative to the **total** positive instances of the test case:

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

- **F1-Score:**

$$F1 - score = 2* \frac{Precision*recall}{Precision + recall} \tag{4}$$

During the experiments, we have considered the following parameters shown in Table 4:

4.2. Dataset

Training a model for leaf disease classification requires a dataset that includes examples of both healthy and diseased leaves. The website *Kaggle.com* is a hub for data science courses and contests. We collected image data from such a competition to validate our proposal called **plant-village** (kaggle, 2018). We extracted three datasets from the original set of 10,000 images with 1,000, 3,000 and 6,000 images, respectively. The labeled images were divided into two sets: one containing 80% of the data for training the model and the other containing 20% of validation or testing data. Some sample images is shown inFig. 3.

Table 5
Accuracy results of Experiment-1.

Model Name	Training Loss	Training Accuracy	Validation loss	validation Accuracy
Simple CNN	0.3430	89.06%	0.2546	87.50%
VGG16	0.1501	95.48%	0.2850	91.08%
VGG19	0.1402	93.28%	0.2751	92.18%
ResNet-50	0.0212	94.38%	0.2654	93.51%

Table 6
Accuracy results of Experiment-2.

Model Name	Training Loss	Training Accuracy	Validation loss	validation Accuracy
Sequential	0.1549	95.00%	0.1646	95.31%
VGG16	0.1429	96.56%	0.3269	91.93%
VGG19	0.1721	95.16%	0.2943	92.45%
ResNet-50	0.1247	95.14%	0.0987	96.55%

Table 7
Accuracy results of Experiment-3.

Model Name	Training Loss	Training Accuracy	Validation loss	validation Accuracy
Sequential	0.0409	98.44%	0.1477	98.21%
VGG16	0.1218	96.03%	0.3484	91.91%
VGG19	0.0871	97.13%	0.1439	93.47%
ResNet-50	0.0711	95.84%	0.2143	96.51%

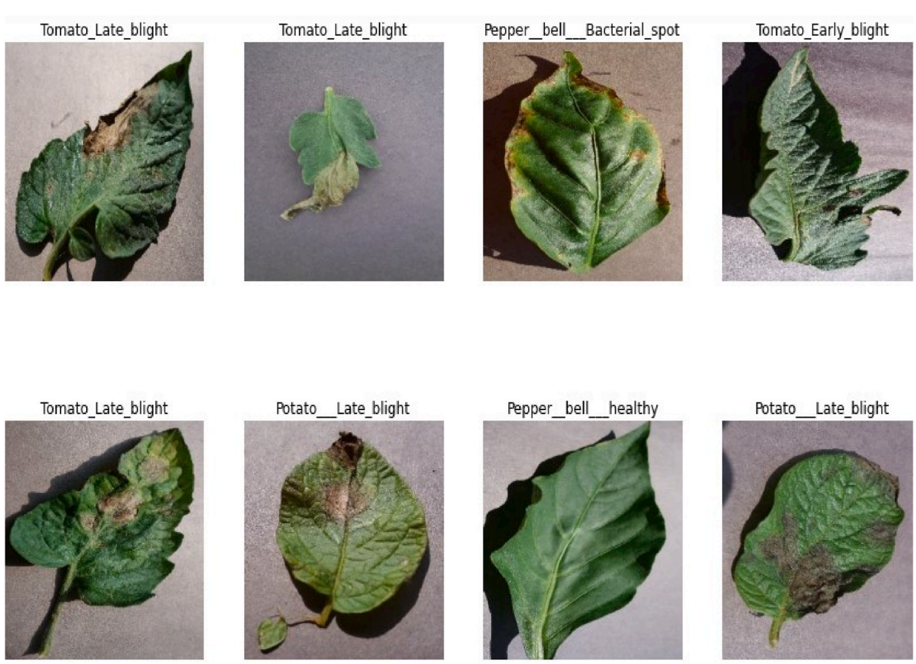
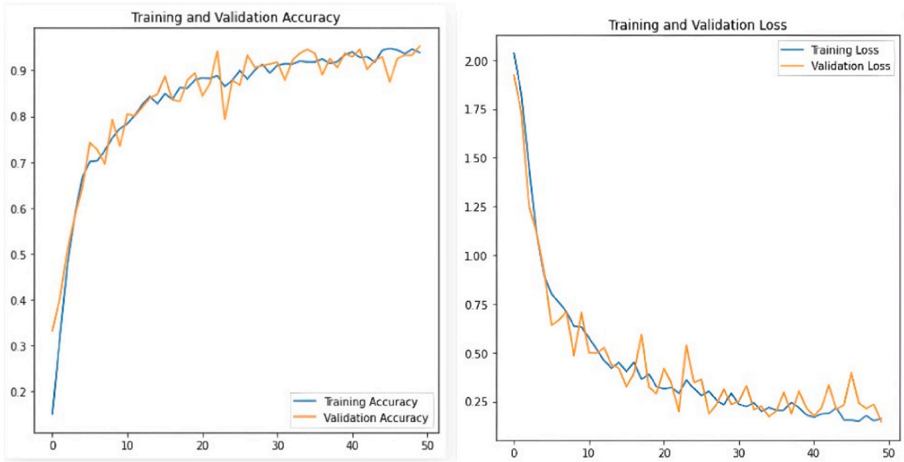


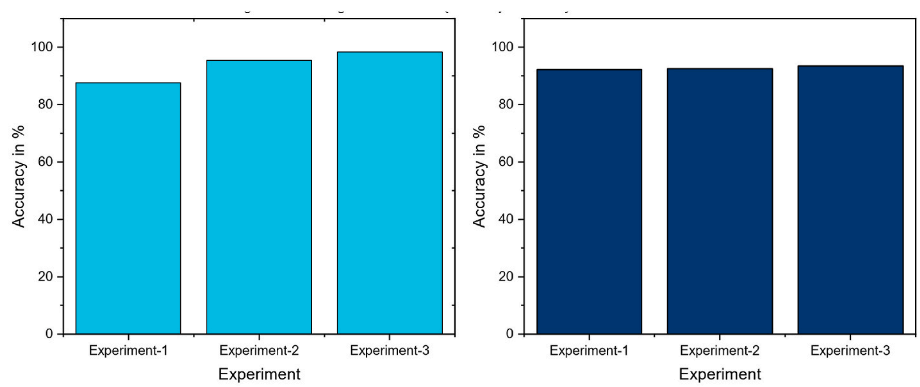
Fig. 3. Examples of Diseased image.



(a) Accuracy curve vs epoch.

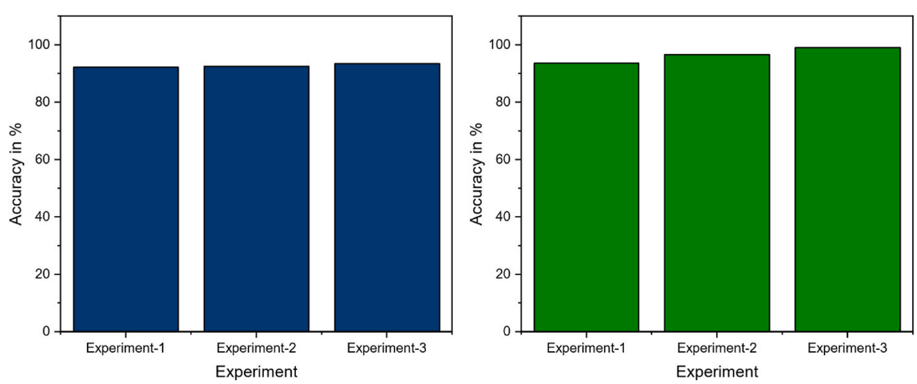
(b) Loss curve vs epoch.

Fig. 4. Training and validation (accuracy and loss) ResNet-50.



(a) CNN

(b) VGG-16



(c) VGG-19

(d) ResNet-50

Fig. 5. Accuracy results.

4.3. Results analysis

Table 5–7 summarizes the average training and validation accuracy and loss for the three experiments.

For any deep learning algorithm, learning curves represent the learning capabilities during the training concerning the dataset in an incremental fashion. With the increasing number of epochs, the training accuracy accurately interprets how well the model is learning with the training dataset. The validation accuracy, on the other hand, provides a prediction of the model's generalizability based on a hold-out validation dataset.

Fig. 4 represents the training and validation accuracy and loss respectively of ResNet50. The loss curve represents that the validation loss and training loss decreased over time and the time between them is minimal during the experiments though we found little fluctuation during the validation test. Fig. 4 shows the training and validation accuracy and loss for the proposal. The validation and training accuracy curves in 4 depict that the accuracy performance is increasing with the training time although the validation curve shows some fluctuation. The loss graph on the other hand represents good fitting as both the training and validation of loss curves are suited well with almost no difference between them.

Table 8
Set-wise accuracy results.

Model	Experiment-1	Experiment-2	Experiment-3
Sequential	87.50%	95.31%	98.21%
VGG-16	91.08%	91.93%	91.91%
VGG-19	92.18%	92.45%	93.47%
ResNet-50	93.51%	96.55%	98.98%

Table 9
Testing results summary of Experiment-3.

Model	Testing Accuracy	Precision	Recall	f1score
Sequential	98.60%	96.83%	98.70%	97.68%
VGG-16	92.39%	93.55%	94.51%	95.71%
VGG-19	96.15%	96.42%	97.06%	96.60%
ResNet-50	98.99%	98.96%	99.05%	98.98%

Fig. 5 presents the performance results of the suggested model in terms of accuracy for different experiments. The accuracy results of any models are growing with the increasing number of images and we found the accuracy of ResNet50 model outperforms the others shown in Table 8.

Table 9 represents the summary results considering accuracy, precision, f1-score and recall of experiment-3. From the table, it is also clear that for any model ResNet50 outperforms the other model. To validate the experiment by ResNet50 more properly, we applied 5-fold cross-validation approach on each of the experiments when we deal with the ResNet50 model. Therefore, in that case, 80% data are used for training cases and the rest of 20% for testing purposes. Fig. 7 depicts the performance results (accuracy) on each of the folds. By averaging the accuracies of each fold we got average accuracy of 93.13%, 96.126% and 98.288% on experiments 1, 2 and 3 respectively.

We focus on three major crops in this study: tomatoes, potatoes, and peppers the three most important crops in Bangladesh. Fig. 6 shows the summary of different leaves considering the accuracy performance of each of the models during the 3 experiments. From the graphs, it is clear that the detection accuracy of ResNet50 is higher than any models for any experiments. 6(d) shows the average accuracy of the models in each experiment. According to our findings the average accuracy for any kind of crop leaves, average accuracy for experiment 3 is better. This is due to the fact that the accuracy performance rises in a linear fashion with the size of the training set.

Fig. 8 represents the confusion matrix for the CNN model for the testing case

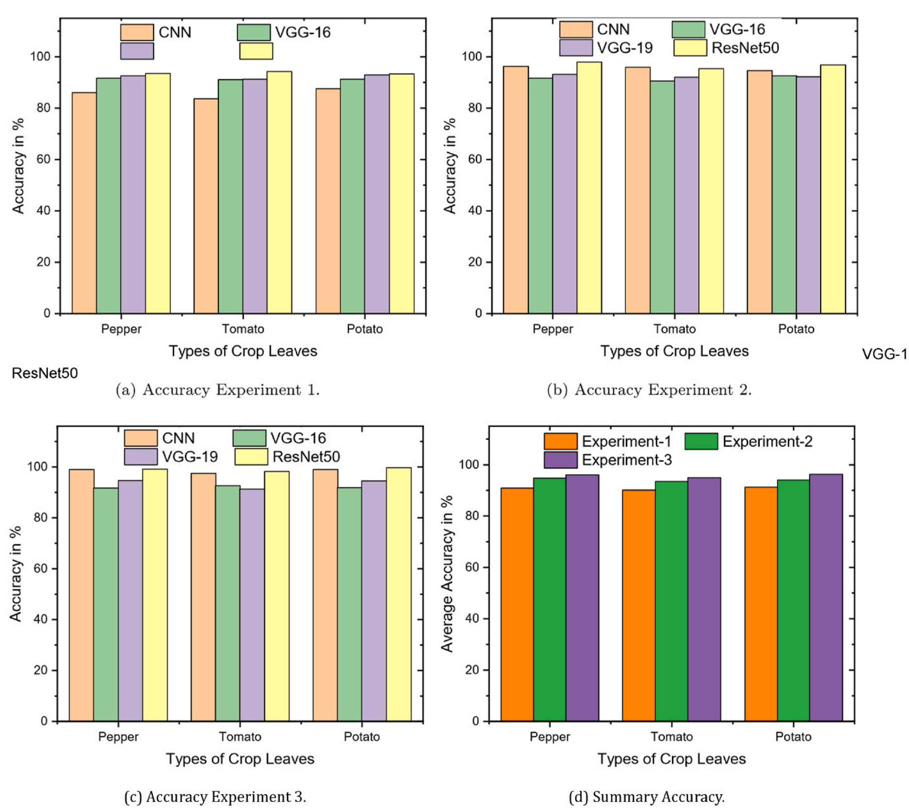
4.4. Discussion

In this research, several deep transfer learning models for crop leaf detection have been proposed. The proposed work is tested on extensive data sets to identify multi-crop leaves.

We investigate the performance of three well-known transfer learning models VGG-16, VGG-19 and ResNet50 to efficiently classify leaf diseases. According to our findings, ResNet50 provides better performance over the two models. The classical VGG-16 and VGG-19 are two of the popular image classification models consisting of 16 and 19 layers respectively. Nevertheless, both models are unable to effectively mitigate the challenge of vanishing gradients, consequently yielding accuracy levels that do not meet the acceptable threshold. In contrast, ResNet50 successfully addresses this problem and significantly reduces testing errors in experimental scenarios. Therefore, this model exhibits enhanced performance capabilities, surpassing the aforementioned models.

Significantly, the proposed model acquired better performance than other state-of-the-art works, as presented in Table 10.

From the Table 10, [29,36,40] worked with a CNN-based approach where they used tomato leaf and multi-crop leaf respectively for their experiments. Though their accuracy was pretty satisfactory, their dataset was small. In that case, our proposed model, when worked with a



(a) Accuracy Experiment 1.

(b) Accuracy Experiment 2.

(c) Accuracy Experiment 3.

(d) Summary Accuracy.

Fig. 6. Crop-wise accuracy results.

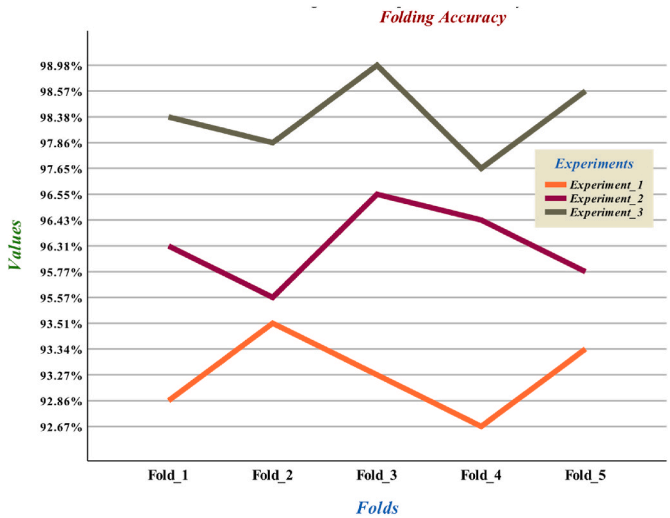


Fig. 7. Folding accuracy results on every experiment applying 5-folding cross validation approach.

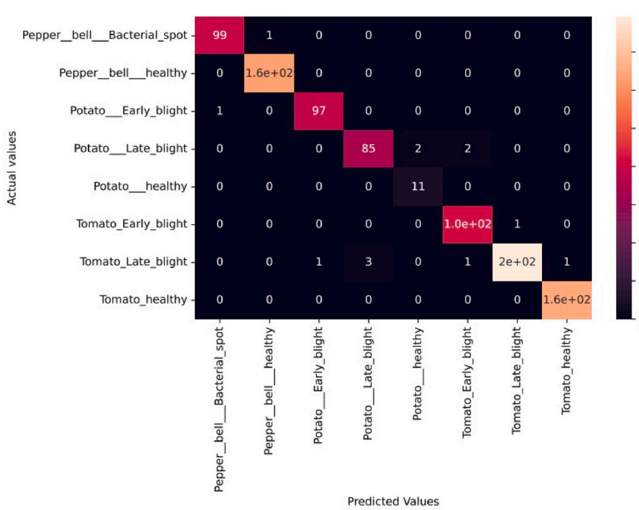


Fig. 8. Confusion matrix for sequential CNN.

large dataset and a CNN-based approach, achieved a better accuracy of 98.60% compared to theirs as shown in Table 10. Nalini et al. [35] suggested deep neural networks architecture with a small number of classification categories, whereas our proposed model used an extensive dataset with 8 classification categories and achieved better accuracy, as depicted in Table 10. Again, from Table 10, [13,32,33] suggested various deep learning approaches for the identification of crop leaf whereas they did their experiment on a single object (i.e., Citrus leaf, Apple leaf, Potato leaf respectively). Furthermore, the dataset for this work [32] was small, as was the classification category [13]. In comparison to these studies, our proposed study deals with multi-crop leaf objects using a large dataset and acquiring better accuracy as shown in Table 10.

5. Web application development

In this research, we also developed a web tool illustrated on Fig. 9 based on the effectiveness results to assist farmers in remotely diagnosing ailments and selecting relevant treatments. Flask is a simple Python framework for creating web applications. It enables the creation and operation of deep learning-based solutions that can aid in the prognosis of plant leaf diseases for end users. Based on real-time data,

Table 10
Performance comparison of with existing related researches.

Study	Object	Total no. of images	Class	Models	Accuracy (%)
[[32]]	Citrus leaf	609 images	5	VGG-19, VGG-16 & Inception-v3	89.5%
[[33]]	Apple leaf	2462 images	6	DenseNet-121	93.71%
[[13]]	Potato leaf	2152 images	3	VGG-19	97.8%
[[29]]	Tomato leaf	736 images	4	CNN based approach	98.12%
[[35]]	Paddy leaf	120 images	2	DNN-CSA	96.96%
[[36]]	Citrus leaf	598 images	4	Two-stages deep CNN model	94.37%
[[40]]	multi-crop leaf	900 images	5	CNN based approach	97.50%
Proposed model	multi-crop leaf	10000 images	8	CNN VGG-19 VGG-16 ResNet-50	98.60% 92.39% 96.15% 98.98%

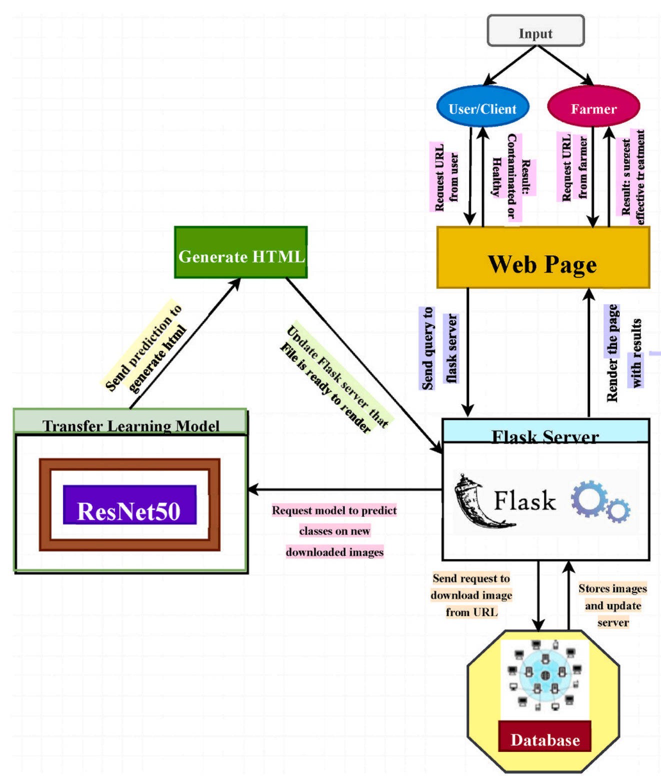
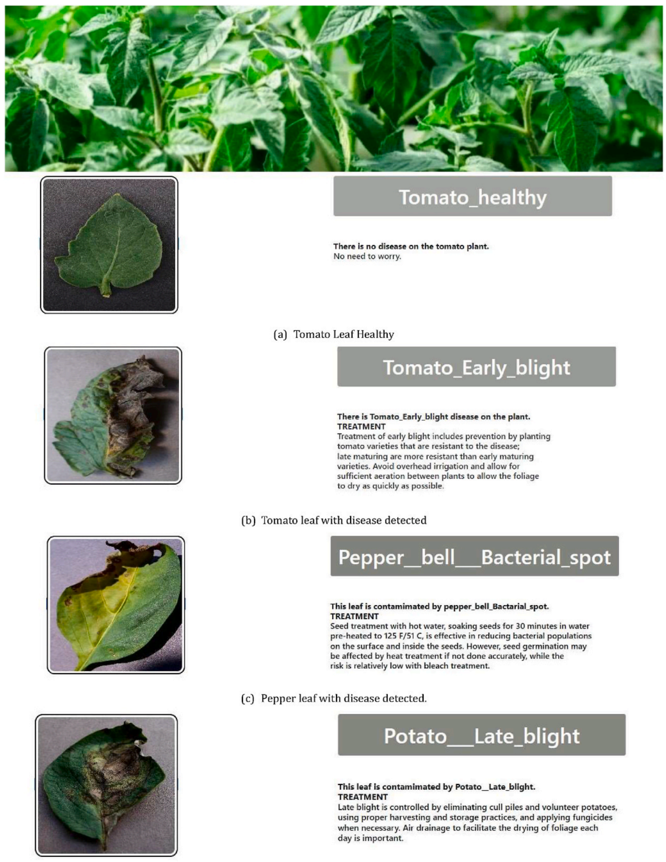


Fig. 9. Proposed web application workflow diagram.

this application can execute the learned algorithm to provide predictions. We used the ResNet50 model in our application, which provides the best accuracy among the others models. We created a web app that would operate on localhost and collect photographs of plants (diseased or normal) from clients before running the model to determine if the plants are infected or healthy.

Our app will take a photo from the user, then resize it to fit the model requirements. The model will check and determine the appropriate class for the photo. Finally, the model informs the user whether the plant in



(a) Tomato Leaf Healthy

(b) Tomato leaf with disease detected

(c) Pepper leaf with disease detected.

(d) Potato leaf with disease detected.

Fig. 10. Web application prediction results
(a) Tomato Leaf Healthy, (b) Tomato leaf with disease detected, (c) Pepper leaf with disease detected, (d) Potato leaf with disease detected.

the photo is contaminated or healthy, and for the former, suggests effective treatment for the disease. Fig. 10 represents the Web Application detection results. This figure indicates the effectiveness of the proposal. represent the Web App detection results.

By utilizing this automatic web application, normal users or clients can get results about disease or healthy leaf information. In the case of farmers, they not only get healthy or disease leaf information but also get effective suggestions for leaf treatment. Furthermore, the farmer will receive a very useful system for the effective identification of plant disease and will be able to take the required steps to avoid losing productivity and perform much better in the agriculture production fields.

6. Application areas of the proposed work

This research is noteworthy because of the contributions it makes to agricultural research its potential application can be summarized as follows:

- AI-enabled leaf disease detection system: This proposal creates an opportunity to quickly and accurately identify diseased leaves by integrating a deep learning model. Our research improves the accuracy of predicting diseases. This can help experts make more accurate diagnoses, which in turn can improve harvest results.
- Automated preventive measures: The results of this study have practical applications in any environment where a web browser is available. By promptly uploading images of diseased crops, farmers can take corrective measures to enhance agricultural productivity.
- Advancement in machine learning techniques: Our research aids the development of deep learning models for use in the smart agricultural industry of any country. The findings of this research can be used to improve crop disease prediction and prognosis using deep-learning models that are both accurate and easy to interpret.

7. Conclusions

Plant and Leaf disease detection and classification problems are crucial and challenging problems in agriculture worldwide. This study utilized Convolutional neural networks-based architecture to identify leaf disease and its source. Several models, such as CNN, VGG-16, VGG-19, and ResNet-50 architectures, are adopted to detect leaf conditions. Extensive experiments were conducted with the freely available "plant-village" plant disease dataset. In the experiment, we got the accuracy rate of 98.60%, 92.39%, 96.15%, and 98.98% for CNN, VGG-16, VGG-19 and ResNet-50 models respectively. Among all models, RestNet50 provides a better accuracy rate to detect leaf disease efficiently. So, we employed the proposed higher accuracy model for our web app development to correctly detect plant leaf disease. The web application provides a smart agriculture system for detecting the disease. Hence, the proposed method produced better outcomes for estimating symptom severity than earlier investigations of plant leaf disease.

In the future, we want to improve the accuracy rate by developing a new hybrid deep-learning architecture using an attention-based mechanism as well as plant leaf disease area identification or developing a localization method to identify the area of disease in the leaf. Besides, we will use better multiple-leaf disease datasets so that it includes all the plant-leaf diseases.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

No data was used for the research described in the article.

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