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Research Article

Prediction of Cotton and Tomato Leaf Disease using Ensemble Learning Algorithm

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Abstract: Agriculture, one of the primary and basic need for living, plays a vital role in the global economy. With growth in newer technology, plants are also more susceptible to new and divergent type of diseases. This type of disease affects the plants leaves and ultimately decreases its yield. This research paper focuses on industrial crop Cotton and food crop Tomato diseased leaf prediction by the framers. It classifies six varieties of cotton leaf diseases and ten varieties of tomato leaf diseases. The approach leverages image processing techniques, transfer learning with CNN techniques and ensemble techniques to classify images of cotton and tomato plant leaves. The main motivation of this research work is to help the farmers predict healthy and infected plant leaves in their farm land with the motivation of implementing sensors in their field. It also encourages future generations to be aware of such diseases in plant leaves and help to eradicate such fungal and viral disease in plants.

Keywords: Cotton and Tomato leaves, Disease Prediction, Digital Image Processing, CNN, Transfer Learning.

1. Introduction

Agriculture engages nearly half of the workforce in the country. It is foremost producer of a variety of crops. It is consistently growing each year. India gives 25% of the world's pulses, 22% of the world's rice, and 13% of the world's wheat in 2013, compared to other countries. Almost 25% of the total quantity is given for cotton production, and it was also the second-highest cotton exporter throughout the previous few years [1].

Leading crops cultivated worldwide is Cotton and Tomato. These plants are integral crops in entire food chain. They are utilized to give food and non-food products, such as ketchup, clothing, and, oil. However, inclined to bacterial, fungal and pathogen diseases [2],[3]. Fungicides are often used in disease control measures. But they are costly and have negative result on the environment. Plant diseases can radically reduce crop yield, quality, and benefit [4]. Timely exploration of diseases educates the farmers to take appropriate actions. Also, minimizes crop damage and prevent further dissemination. Manual examination of plant leaves is time-consuming and ends up with errors. Hence, mechanical system is needed to identify plant diseases [5]. The usage of machine learning and computer vision techniques to create automated systems for cotton disease prediction has gained popularity in recent years.

Convolutional Neural Networks (CNNs) are under deep learning neural networks created especially for exploring visual inputs, like images or videos. They are made up of a number of layers, including fully connected, pooling, and convolutional layers depicted in Figure 1[6]. These layers adapt the input data using a group of learnable filters known as kernels. Pooling Layers cut the input's spatial dimensions while keeping the crucial details. Fully Connected Layers complete the final classification or regression tasks and are often inserted at the conclusion of the CNN. They link every neuron in the layer below to every neuron in the layer above. In order to produce predictions, fully connected layers combine the spatial information acquired by prior layers.

Transfer learning is a technique that entails using the information gained from previously trained models on one task and applying it to another, similar activity. Combining transfer learning with CNNs (Convolutional Neural Networks) is a common practice. It gains knowledge from low and high level learned feature to image based problems. This method is suitable for small dataset or when the work is similar to the original task on which the pre-trained model was trained.

Ensemble learning combines multiple individual models, called base models or weak learners, to form a more accurate and robust predictive model. The idea behind ensemble learning is that by aggregating the predictions of multiple models, the ensemble can often outperform any individual model.

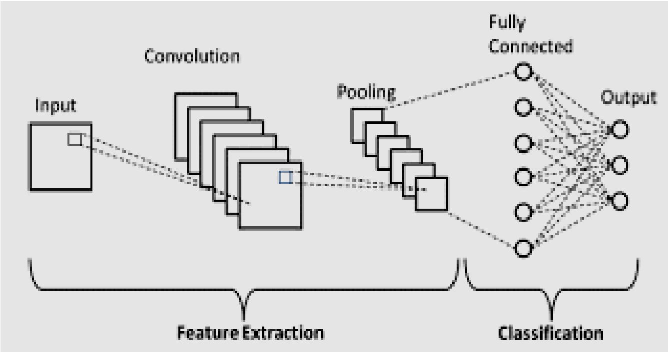

Figure 1: Convolution Neural Network [6]

This paper discusses about the previous works carried out in section 2, various methods and techniques in section 3, performance metrics and results in section 4 and finally the conclusion in section 5.

2. Related Work

A wide variety of computer vision-based plant disease detection and classification algorithms are being discussed in this literature review. The first section of literature review summaries the most recent studies on cotton disease prediction. Next section summaries about Tomato leaf disease prediction.

Zekiwos, M et al. [7] developed a model to detect diseased cotton leaf and pest using deep learning technique. The main goal of their work is to create a model to improve the identification of pests and diseases affecting cotton leaves using CNN's deep learning method. The researchers have done this by using prevalent pests and diseases that affect cotton leaves, including bacterial blight, spider mites, and leaf miners. The dataset splitting technique of K-fold cross validation was used to increase the generalization of the CNN model. Nearly, 2400 specimens (600 photos in each class) were retrieved. It achieves 96.4% accuracy.

Kumbhar, Shantanu, et al. [8] proposed a system which is used to identify cotton leaf disease. The authors used convolutional neural network (CNN) to predict cotton disease. They focused on Alternaria Macrospora and Bacterial Blight. Although the authors achieved 80% accuracy, they used limited data and concentrated only on two types of diseases which is a major drawback.

Jenifa, A., et. al [9] used Deep Convolutional Neural Network based approach for automatic prediction of Cotton leaf diseases. Although the authors achieved an average accuracy of 96 %, the limited amount of data and technically backward limits their progress.

Patil et al. [10] extracted colour and texture of cotton leaves. The authors later fed into machine learning algorithms. Four colour features and eight texture features were considered and performed analysis using only colour features, only texture features, and both colour and texture features. The authors found that colour features were enough to classify the leaves into health and unhealthy. Although the authors achieved an average accuracy of 94% with respect to colour. Both colour and texture features are important for considering whether a leaf is healthy or not which is to be considered.

Vasavi et al. [11] identified crop leaf diseases with the help of five major steps like Image acquisition, pre-processing, segmentation, feature extraction and classification. Although the authors tried to enhance the importance of integrating computer vision, machine learning, deep learning to the automated devices like UAVs, smart mobiles in the era of agriculture. Lack of sufficient dataset isa major drawback.

Azfar, Saeed, et al. [12] used IoT technology and drones indeed a step towards modernization. Pest monitoring and identification is being conducted through these technologies. The authors framed an IoT framework to find insects with the help of motion sensors. The motivation behind their work is to modernize pest management, increase the quantity and quality and profit.

Mim, Tahmina Tashrif, et al. [13] used AI algorithms, specifically convolutional neural networks (CNN), combined with computer science and image processing techniques to develop a system that can accurately classify and predict tomato leaf diseases. The system allows farmers to input images of affected tomato leaves as symptoms, and it predicts the specific disease. The research paper identifies six different classifications of tomato leaf diseases, including a healthy class. The system achieved an accuracy rate of over 96.55% in disease prediction. By implementing this user-friendly system, the researchers aim to reduce the use of harmful chemicals and pesticides in agriculture.

Thangaraj, Rajasekaran, [14] et al. shows the importance of accurately and quickly identifying tomato plant diseases to improve agricultural productivity. Traditionally, human experts have been relied upon to identify anomalies in tomato plants caused by pests, diseases, climate, and nutrient deficiencies. However, conventional image processing and machine learning approaches have yielded lower accuracy in automatic tomato leaf disease identification. To improve prediction accuracy, this research paper introduces deep learning-based classification methods.

Ashok, Surampalli, et al. [15] proposed a method for identifying tomato plant leaf diseases using image processing techniques, specifically image segmentation, clustering, and open-source algorithms. By utilizing these techniques, the authors developed a reliable, safe, and accurate system for detecting leaf diseases, with a particular focus on tomato plants. It also highlights the significance of early detection and the potential benefit for the agricultural economy.

Agarwal, Mohit, et al. [16] discusses a deep learning-based approach for detecting and classifying diseases in tomato crops. The proposed model uses a Convolutional Neural Network (CNN) architecture, which consists of three convolutional layers and three max pooling layers, followed by two fully connected layers. The experimental results show the impact of the proposed model. The classification accuracy of the model ranges from 76% to 100% for different classes, with an average accuracy of 91.2%. As a future work, the researchers aim to enhance the model by incorporating a larger number of images and expanding the scope to include other crops besides tomatoes.

Basavaiah, Jagadeesh, and Audre Arlene Anthony [17] developed a technique for identifying leaf diseases in tomato plants in order to prevent losses in crop quantity and quality. Their approach focused on improving classification accuracy and reducing computational time. The novelty lies in the fusion of multiple features to enhance classification accuracy. Specifically, colour histograms, Hu Moments, Haralick, and Local Binary Pattern features are utilized for training and testing. To classify leaf diseases, the random forest and decision tree classification algorithms are employed. The decision tree classifier achieves a classification accuracy of 90%, while the random forest classifier achieves 94%. In the proposed work only four main diseases of tomato leaves: bacterial spot, septoria spot, mosaic virus and yellow-curl were detected.

Overall, the recent research on cotton and tomato disease prediction has demonstrated the potential of machine learning and computer vision techniques for early detection and timely management of cotton and tomato diseases. These automated systems can reduce the reliance on manual inspections, improving the accuracy and efficiency of disease diagnosis, and ultimately contribute to the sustainability of cotton production.

3. Experimental Methods

Our proposed model minimizes the time and achieves good accuracy. The inception v3 algorithm, ResNet152 v2, VGG16 and our proposed algorithm were used to train the cotton and tomato leaf disease dataset.

Inception V3 is a well-known CNN algorithm after its predecessor inception V2. It uses pre-trained model InceptionV3 and defined the weights and input image size. Imagenet is used as predefined weight because it uses pre-trained weights which was used to train the inceptionV3 model.It uses parallel convolutional layers with different filter sizes which best represents its efficiency. Flatten property of inception v3 converts the three-dimensional vector (batch size, height, width, channels) into single dimensional vector of batch size and flattened size (product of height, width and channel). Since it is a multiclass problem, softmax activation function is used and categorical cross entropy loss function is used to quantify how well the model's predicted probabilities match the ground truth labels. Adam optimization algorithm is commonly used as the optimizer during the training process. It has a separate learning rate for each parameter, and changes their rate based on historical gradient information. Data augmentation artificially expands the training dataset in order to improve the model's performance. It uses horizontal flipping where the images are flipped horizontally, which helps the model learn features that are invariant to left-right orientation. The accuracy of the model for Cotton leaf disease prediction is97% and for tomato is 84%.

VGG16 consists of multiple stacked convolutional layers, each with max pooling layer. The convolutional layers use small 3x3 filters with a stride of 1, and they are designed to extract features from the input images at different levels. The pooling layers reduce the spatial dimensions of the feature maps while preserving the important information. It undergoes 5 epochs with an accuracy of 98% for cotton and 90% for tomato.

In ResNet-152 V2 model, the activation function is applied before each convolutional layer. This pre-activation design solves the vanishing gradient problem. ResNet-152 v2 has 152 layers, including convolutional layers, pooling layers, and residual blocks. It has been pre-trained on large-scale image datasets like ImageNet. In undergoes five epochs with an accuracy of 99% for cotton and 92% for tomato.

The model proposed above are not sufficient to reach our goal of accuracy. Fuzzy logic also fails under such circumstances [18] So comes the ensemble model depicted in figure 2 which combines multiple models for prediction.

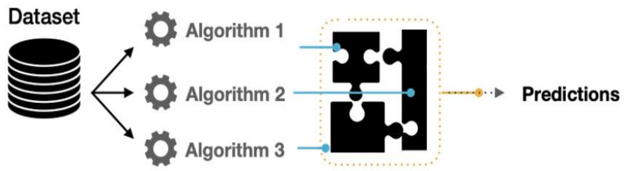

Figure 2: Ensemble Model [19]

After training three different model, the models are combined using Bagging and final model was implemented. The proposed ensemble model produced an accuracy of 99.4% for Cotton and 95% for Tomato.

3.1 Dataset used

This study uses Cotton and Tomato dataset from Kaggle. Cotton leaf disease dataset [20] comprises of six classes with a total of 3118 images captured under real world conditions and from internet. They are Amphids with 520 images, Army Worm with 520 images, Bacterial Blight with 520 images, Healthy leaves with 520 images, Powdery Mildew with 520 images and Target Spot with 518 images. Figure 3 shows some of the diseased cotton leaves.

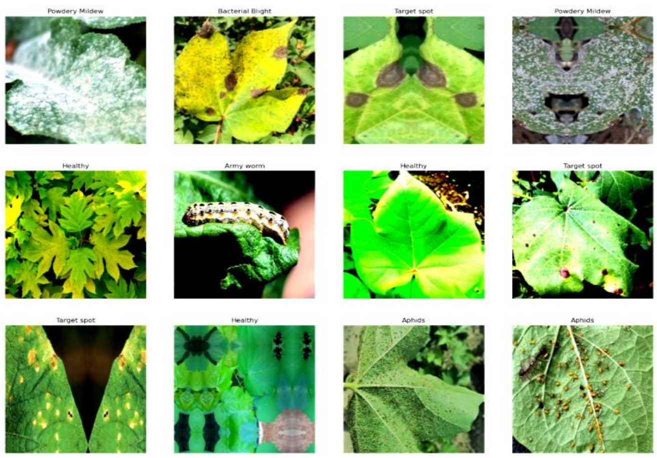

Figure 3: Diseased and Healthy Cotton Leaves

Tomato leaf disease dataset was collected from Kaggle [21]. It classifies nearly ten different types of tomato leaf diseases including healthy leaf. They include Tomato mosaicvirus, Target spot, Bacterialspot, Tomato yellow leaf curl virus, Lateblight, Leafmold, Earlyblight, Spidermites two-spotted spidermite, Tomato healthy, and Septoria leafspot. Each class contains 1000 images for each training and 100 images for validation.A sample of tomato leaf disease is depicted in figure 4.

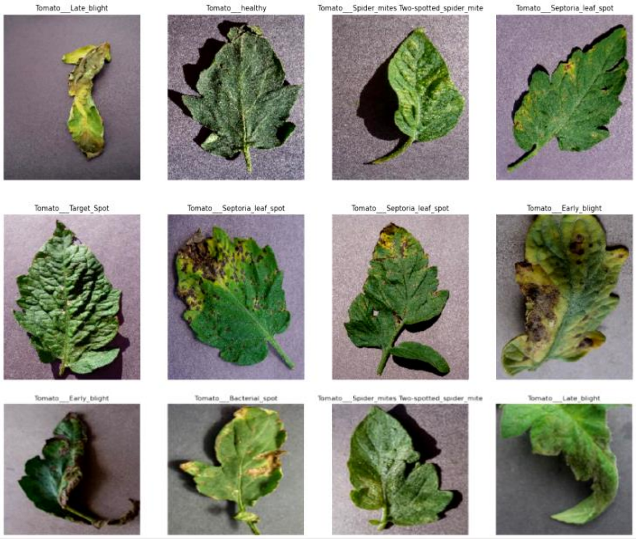

Figure 4: Diseased and Healthy Tomato Leaves

Initially, the dataset is pre-processed to remove unwanted noise. After removing noise, they were rescaled, enhanced and augmented for better clarity. Finally, dataset is divided into training and testing. The distribution of different classes of cotton and tomato leaf disease is given in the figure 5 and figure 6.

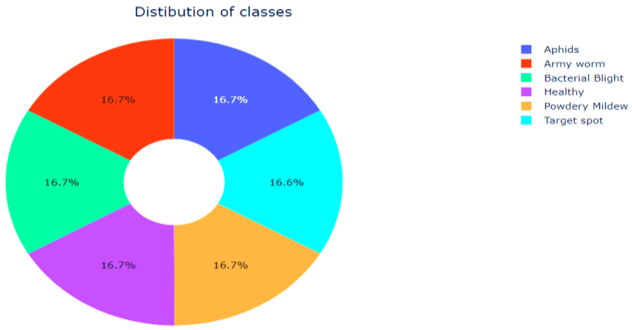

Figure 5: Distribution of classes for Cotton plant

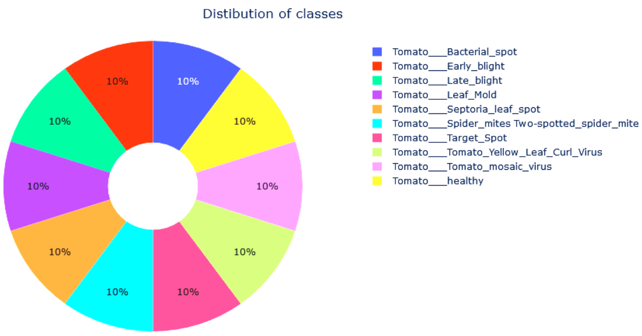

Figure 6: Distribution of classes for Tomato plant

Contribution of different authors and their works discussed in literature survey is summarised in Table 1.

Table 1: .Summary of work done previously

Author	Method used	Crop	Disease Predicted	Accuracy (in %)
Zekiwos, Met al.	CNN Deep Learning, K fold Cross Validation	Cotton	bacterial blight, spider mites, and leaf miners	96.4
Kumbhar, Shantanu, et al.	CNN	Cotton	Alternaria Macrospora and Bacterial Blight	80
Jenifa, A., et. Al	Deep Convolutional Neural Network	Cotton	Cercospora, Bacterial blight, Ascochyta blight, and Target spot.	96
Patil et al.	Support vector machine, Naive Bayes, Random Forest, AdaBoost, K-nearest neighbor, Multilayer perceptron	Cotton	Two Classes Healthy or Diseased	93.38, 90.91, 95.86, 92.56, 94.21, 96.69
Azfar, Saeed,et al.	IoT technology, sensors and drones	Cotton	Multiple pests	--
Mim, Tahmina Tashrif, et al.	AI algorithms, specifically convolutional neural networks (CNN),	Tomato	Six different classes	96.5
Ashok, Surampalli, et al.	Image segmentation, clustering, and open-source algorithms, CNN algorithm for hierarchical feature extraction	Tomato	2 Classes healthy or diseased	98
Agarwal, Mohit, et al.	CNN	Tomato	10 Classes	91.2
Basavaiah, Jagadeesh, &Audre Arlene Anthony	Colour histograms, Hu Moments, Haralick and Local Binary Pattern features are used	Tomato	Bacterial spot, septoria spot, mosaic virus and yellow-curl were detected	90 and 94

The proposed work is illustrated in figure 7. Collected Cotton and tomato leaves from Kaggle were pre-processed to remove unwanted noise and outliers.

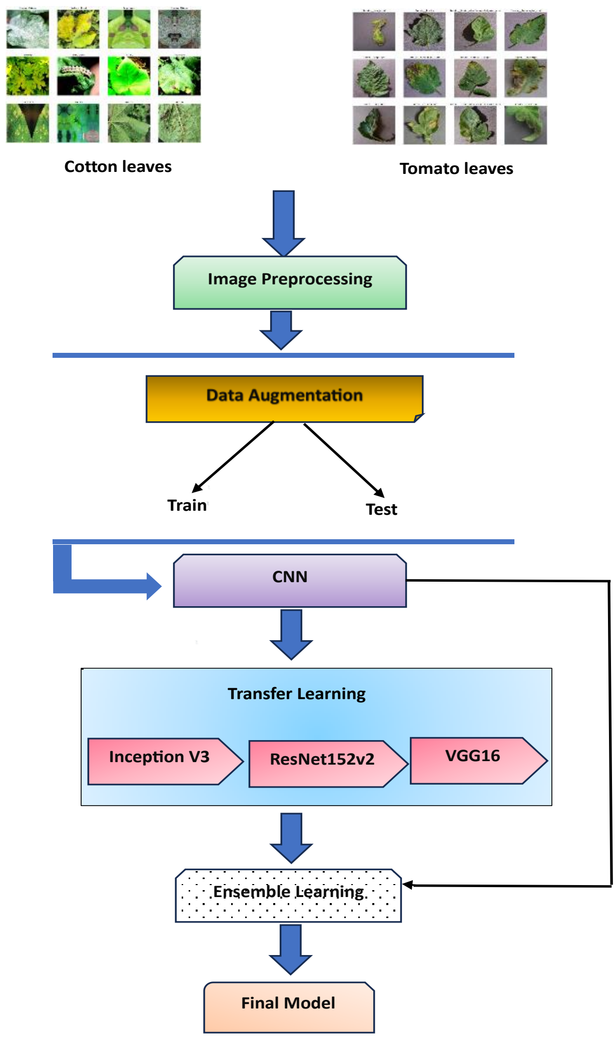

Figure 7: Overall Architecture of proposed work

Numerous image processing techniques were used to remove the outliers. After image processing, data augmentation is done to extract images and split into training and testing data. The model is trained using transfer learning techniques like Inception V3, ResNet152v2 and VGG16. Transfer learning's teaches the initial layers to detect textual features and edge detection of images. As they capture essential aspects of the data, these features can be applied to other activities. Usually transfer learning process include:

3.2 Pre-training

A large-scale image dataset like ImageNet which is labelled, is used to train a CNN model. The model gains knowledge of common visual characteristics and performs well on the pre-training task, such as picture categorization and classification.

3.3 Fine-tuning

Here a smaller labelled dataset is then started, with the pre-trained model as initial point. Upon certain target the weights for the model are kept fixed. Remaining layers are adjusted accordingly to be more suitable for new task. This gives a broader knowledge of all the attributes used. Later ensemble of algorithms is created using Bagging. Finally, our proposed model shows 99.4 % accuracy.

4. Results and Discussion

To find the performance of each model, different parameters were considered. Figure 8 shows the learning curve of inceptionv3, VGG16, RESNET152V2 and the proposed Ensembled model for cotton plant.

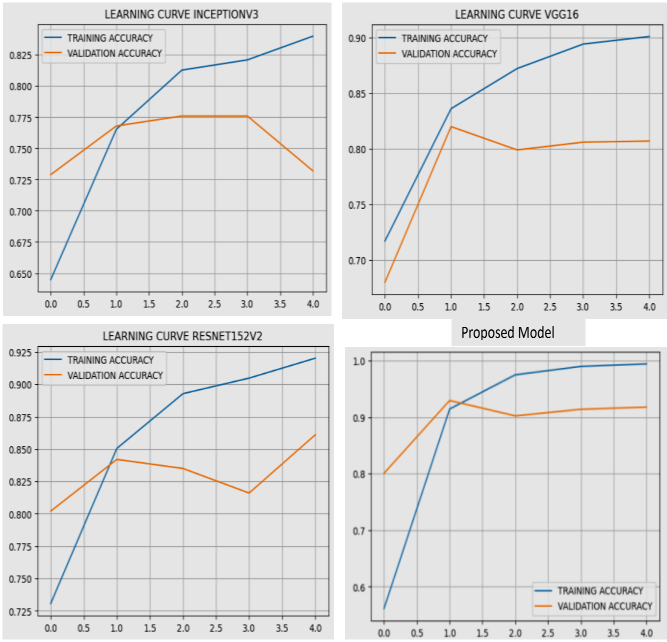

Figure 8: Learning curve of inceptionv3, VGG16, RESNET152V2 and the proposed Ensembled model

The training and validation accuracy of the models for cotton is given in table 2. The validation accuracy assumes to be low compared to training data in our dataset. This is because the model has never seen new data (validated data) before. The inceptionv3 algorithm has 99.44% training accuracy and 91.80% validation accuracy while that of VGG16 algorithm has 99% training accuracy and 94% validation accuracy. RESNET152V2provides has 98.24% training accuracy and 94.23% validation accuracy and our proposed ensemble model has 99.67% training accuracy and 94.87% validation accuracy.

Table 2: Training and validation accuracy of the models for Cotton (in %)

Algorithm	Training Accuracy	Validation Accuracy
InceptionV3	99.44	91. 80
VGG16	99	94
RESNET152V2	98.24	94.23
Ensemble Model	99.67	94.87

Figure 9 shows the learning curve of inceptionv3, VGG16, RESNET152V2 and the proposed Ensembled model for tomato.

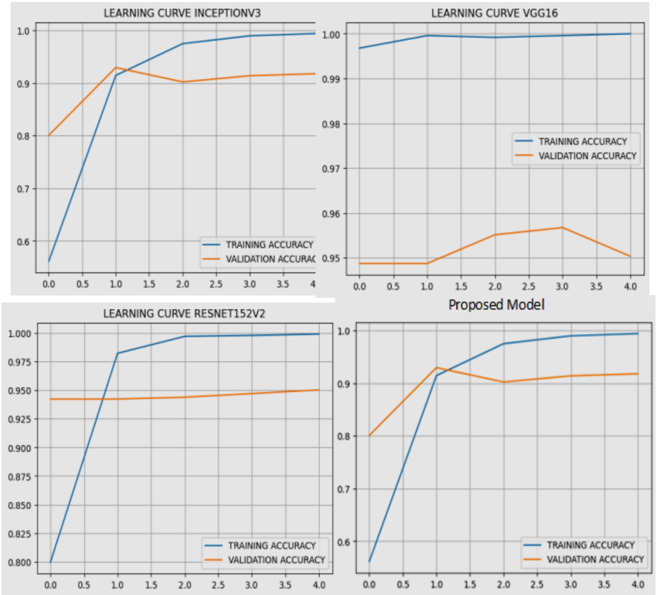

Figure 9: Learning curve of inceptionv3, VGG16, RESNET152V2 and the proposed Ensembled model for Tomato

The training and validation accuracy of the models for tomato is given in table 3. The validation accuracy of tomato is comparatively low to that of cotton. The inceptionv3 algorithm has 84% training accuracy and 73.20% validation accuracy while that of VGG16 algorithm has 90.10% training accuracy and 80.70% validation accuracy. RESNET152V2 provides has 92.02% training accuracy and 86.10% validation accuracy and our proposed ensemble model has 99.62% training accuracy and 93.9% validation accuracy.

Table 3: Training and validation accuracy of the models for Tomato (in %)

Algorithm	Training Accuracy	Validation Accuracy
InceptionV3	84.00	73.20
VGG16	90.10	80.70
RESNET152V2	92.02	86.10
Ensemble Model	99.62	93.9

The proposed model identifies leaf disease at early stage since the features of leaf extracted earlier. The model of different models and the proposed model is given in bar chart in figure 10 and 11.

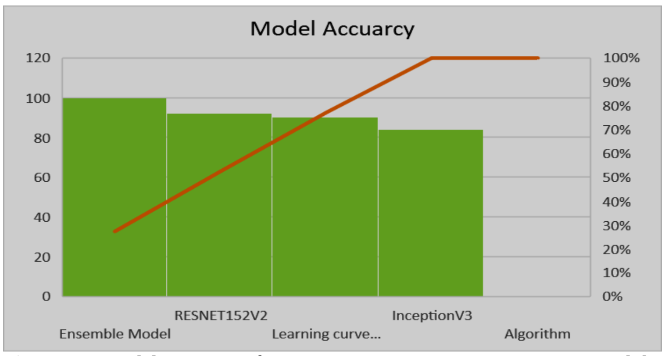

Figure 10: Model accuracy of inceptionv3, VGG16, RESNET152V2 and the proposed Ensemble model for Cotton

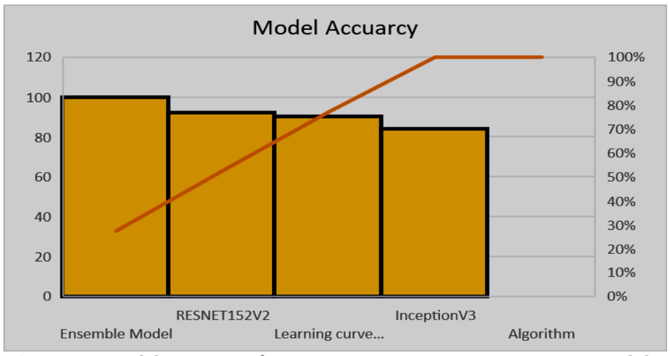

Figure 11: Model accuracy of inceptionv3, VGG16, RESNET152V2 and the proposed Ensemble model for Tomato

A comparison of the accuracy of various machine learning models is displayed in the image. The various models (Ensemble Model, RESNET152V2, InceptionV3, Algorithm) are listed on the x-axis, and the accuracy is represented by the y-axis, which ranges from 0% to 100%.

The following are the main findings from the graph:

Ensemble Model: 100% accuracy is attained. RESNET152V2: 90% accuracy is attained. InceptionV3: Attains 80% accuracy. Algorithm: Although the algorithm's accuracy isn't stated clearly, it seems to be less accurate than the other models. The "learning curve," represented by the orange line, illustrates how the models' accuracy increases with training. The learning curve shows that as the models gain knowledge from the data, their accuracy rises steadily from a low starting point.
The Ensemble Model, which attained 100% accuracy, appears to be the most accurate model overall, according to the graph. RESNET152V2 and InceptionV3, with 90% and 80% accuracy rates, respectively, also exhibit strong performance.
Figure 12 and Figure 13 shows the actual and predicted disease for cotton and tomato plant diseases. Proposed model achieved 99% plus accuracy. This is evident from the experimental results given below and moreover the actual and predicted disease seems to same for almost all the leaves given below.

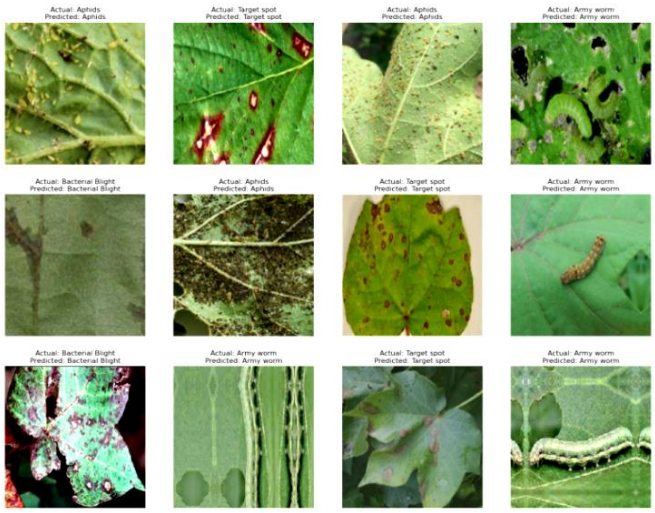

Figure 12: Experimental Results for Cotton

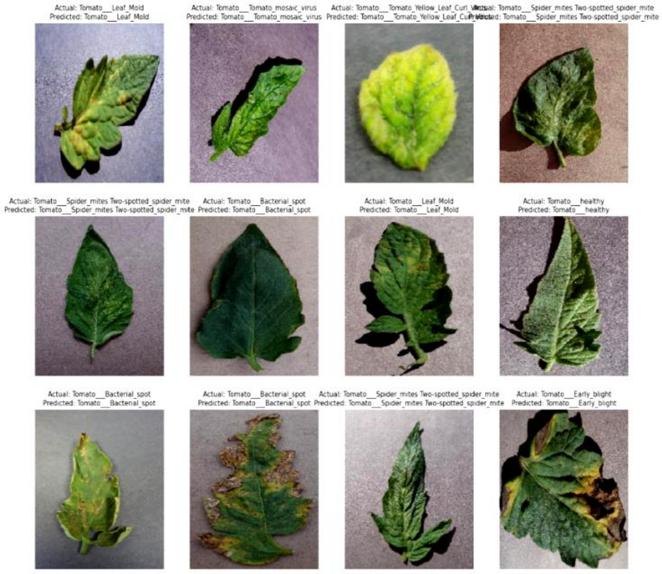

Figure 13: Experimental Results for Tomato

5. Conclusion and Future Scope

Plant disease is dangerous to agriculture and environment. It affects not only individual health but also leads to exhaustion of environment and its area. This paper proposed a ensembled model using transfer learning and CNN to identify plant disease mainly cotton and tomato in advance. It will be more profitable and accountable when we employ the same with sensors in the field. However, farmers could not afford sensors for large hectare of land and moreover sampling of sensor data can be considered. Taking all these points for future consideration ensemble techniques holds the best for the data proposed by the authors.

In the future, the system's efficacy in diagnosing and treating plant illnesses might be increased by incorporating IoT sensors for real-time data collecting, creating an intuitive mobile app, and putting the YOLO algorithm into practice to increase object identification accuracy.

Conflict of Interest

The review paper's authors hereby state that they have no known or potential conflicts of interest with any organizations, companies, or individuals related to the subject matter of this work. We have not received any direct or indirect financial support, or non-financial support, from any parties regarding the subject matter of this review. Our analysis and conclusions are solely based on our independent and unbiased assessment of the available data and research.

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Authors' Contributions

Author 1 produced Python scripts for a variety of modules and functions and led the design and implementation of a machine learning technique. Author 2 supervised the research and gave the project general guidance.

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