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# An ensemble deep learning model for automatic classification of cotton leaves diseases

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**ABSTRACT**

Cotton plant (*Gossypium herbaceum*), is one of the significant fiber crop grown worldwide. However, the crop is quite prone to leaves diseases, for which deep learning (DL) techniques can be utilized for early disease prediction and prevent stakeholders from losing the harvest. The objective of this paper is to develop a novel ensemble based deep convolutional neural network (DCNN) model developed on two base pretrained models named: VGG16 and InceptionV3 for early detection of cotton leaves diseases. The proposed ensemble model trained on cotton leaves dataset reports higher training and testing prediction accuracies as compared to the base pretrained models. Given that, deep learning architectures have hyper-parameters, this paper presents exhaustive experimental evaluations on ensemble model to tune hyper-parameters named learning rate, optimizer and no of epochs. The suggested hyper-parameter settings can be directly utilized while employing the ensemble model for cotton plant leaves disease detection and prediction. With suggested hyper-parameters settings of learning rate 0.0001, 20 epochs and stochastic gradient descent (SGD) optimizer, ensemble model reported training and testing accuracies of 98% and 95% respectively, which was higher than the training and testing accuracies of VGG16 and InceptionV3 pretrained DCNN models.



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## 1. INTRODUCTION

The current focus of artificial intelligence (AI) in agricultural research revolves around the appliance of machine learning (ML) based predictive techniques for improving productivity and sustainability of the agricultural output [1]. ML techniques have demonstrated their potential in the early detection of numerous crop diseases, thereby offering valuable insights to farmers and other stakeholders. This proactive approach enables timely interventions, mitigating the risk of substantial losses in agricultural production.

The cultivation of *Gossypium herbaceum*, commonly known as the cotton plant, holds immense importance as a fiber crop on a global scale, being cultivated in numerous countries across the world. The agricultural cultivation of this particular crop predominantly revolves around the cultivation of its delicate and voluminous bolls, which intricately envelop the seeds. These bolls are subsequently processed to yield refined cotton threads. Throughout the annals of history, cotton has steadfastly remained the quintessential fiber of choice for humanity, serving as the cornerstone for the production of clothing and textiles. Cotton, as an agricultural commodity, exhibits a remarkable capacity to bolster the economic prosperity of a nation [2].

The cotton plant exhibits a notable susceptibility to bacterial and viral infections, which can be discerned through the observation of its leaves. Examples of such infections include bacterial blight, cotton leaf curl disease, and fussarium wilt, among others. These diseases have been observed to inflict significant damage upon cotton plants. To optimize crop productivity and enhance cotton quality, it is imperative to proactively safeguard cotton plant against potential diseases. Farmers and other stakeholders employ a range of plant medications and pest management techniques to mitigate the impact of microorganisms on crops. The utilization of information assisted technologies has demonstrated significant advantages in aiding farmers to proactively address various factors, enabling the monitoring of plant health and providing real-time recommendations to mitigate the impact of plant infections [3]. Several cutting-edge techniques can be enumerated, such as the utilization of robotics in agricultural practices, the application of ML based algorithmic techniques for accurate weather forecasting and disease prediction and the automation of soil quality evaluation. In recent times, there has been a notable trend in employing convolutional neural network (CNN) trained deep learning models, for the purpose of training and constructing disease prediction models in various plant species. The primary objective is to facilitate ML in order to identify and comprehend the distinguishing characteristics of various leaf diseases. Subsequently, these acquired models are deployed in real-time scenarios to anticipate diseases and provide timely alerts to farmers. Nevertheless, it is worth noting that several studies indicate that the predictive capabilities of models trained on deep learning network architectures may demonstrate varying degrees of accuracy when applied to plant species that differ from those used for training purposes. Therefore, it is imperative to optimize and reassess pretrained models in relation to particular plant species, enabling the adjustment of parameters specific to the plant of interest prior to implementation. Given the considerable importance of the cotton plant in the national economy, it becomes imperative to employ ML techniques, specifically CNN pretrained models, to effectively address the issue of real-time detection of diseases affecting cotton plant leaves. Brahimi *et al.* [4] employed a dataset comprising 14,828 high-resolution images of tomato leaves exhibiting symptoms associated with nine distinct disease categories. The level of accuracy exhibited by this model surpasses that of shallow models significantly.

In another study by Pattnaik *et al.* [5] development of a system utilizing deep convolutional neural networks (DCNNs) for classifying pests that commonly infect tomato plants was done. The researchers employed a total of 859 images depicting various types of pests, which were classified into 10 distinct categories. Among the 15 pretrained models evaluated, it was found that the DenseNet169 model exhibited the best accuracy levels for classification, achieving a notable value of 88.83%. A deep learning-based method was created in a different study by Hu *et al.* [6] to identify tea leaf blight (TLB) disease and severity diagnosis. The researchers improved the original photographs and reduced the impact of shadows and light variation using the retinex algorithm. Successful TLB leaf recognition is achieved using the faster region deep learning convolutional neural networks (Faster R-CNN). In another research, Karthik *et al.* [7] suggested two other deep learning models for the identification of diseases in tomato leaves. The first architecture utilised residual learning for collecting significant information to aid in classification, but the second architecture used an attention mechanism over and above residual deep network. In experiments, the three diseases named as late blight, leaf mold and early blight are categorized by the plant village dataset. The results show that the attention mechanism was successful in achieving validation accuracy of 98% using fivefold cross-validation. Hernández and López [8] developed a probabilistic programming-based technique for identifying plant illnesses. Their approach used uncertainty metric for quantifying misclassifications using deep learning algorithms based on Bayesian classification.

Kumar *et al.* [9] developed a method for disease prediction in tomatoes based on the nature inspired 'whale optimization based artificial neural network (WOANN)'. The proposed WOANN-based system obtains improved accuracy and outperforms conventional disease prediction techniques, demonstrating promising results. Many other researchers [10]–[13], also used nature inspired optimization along with deep learning for plant disease classification. Applications of varied other ML techniques for plant diseases classification can be found at [14]–[16]. Sachdeva *et al.* [17] proposed a deep CNN model using a Bayesian learning technique. The researchers employed a total of 20,639 photographs sourced from the plant village dataset, encompassing 15 distinct categories of afflicted bell pepper plants, potato and tomato plants. The experimental findings supported the developed model's effectiveness in accurately classifying diseases. Several previous studies [18]–[22] have also utilized CNN models with modifications to identify different types of plant leaf diseases across different plant categories.

Research gap and contribution of conducted research: the existing body of research has extensively examined the many applications of DCNN models in the detection of diseases in plant leaves. However, there is a lack of extensive experimentation conducted on the utilization of ensemble models comprising deep pretrained CNN architectures. Furthermore, it is evident from the existing literature review that there is a significant gap in study on the training and optimization of CNNs for the purpose of detecting diseases in cotton plant leaves. This particular aspect has not been thoroughly investigated by scholars in the field. Therefore, this study introduces an innovative ensemble CNN model for the identification of diseases in cotton leaves.

The ensemble model is constructed by utilizing the learning methodology and parameters obtained from two pretrained models, namely VGG16 and Inception V3. The utilization of ensemble techniques has led to a substantial enhancement in both training and testing accuracies. The study focuses on conducting experiments that explicitly explore the hyper-parameter tuning and training of an ensemble CNN model. The experiments are conducted using a dataset consisting of cotton leaves images extracted from the plant village dataset [23]. This model has the potential to be applied in mobile applications, specifically designed to aid farmers in the real-time diagnosis of cotton leaf diseases before they become severe.

## 2. METHOD

The presented study showcases a novel ensemble machine learning model for the precise prediction of diseases in cotton plants based on leaf characteristics. Ensemble models employ meta-learning methodologies to enhance their training process [24]. Meta-learning approaches refer to methodologies that strive to enhance the capabilities of numerous foundational machine learning models [25]. This is achieved by amalgamating the acquired features of these models and constructing a novel model that encompasses the most optimal interpretations derived from the foundational models. Various methodologies can be implemented to cultivate ensemble models, with bagging, stacking, and boosting being the foremost techniques. In this conducted research study, bagging has been employed to construct an ensemble model comprising of two pretrained CNN models, namely VGG 16 and Inception V3, as depicted in Figure 1.

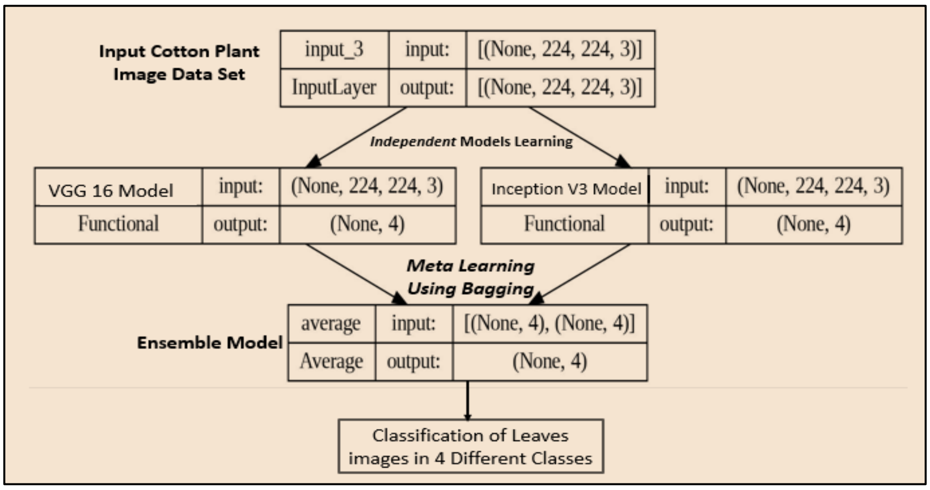


Figure 1. Ensemble model generation approach

In the context of agricultural research, an input image dataset is utilized to train two primary models. These models are initially trained individually, and subsequently, the features acquired by these base models are combined through a process known as bagging. This aggregation of features results in the creation of an ensemble model, which holds significant potential for enhancing agricultural research outcomes. The bagging methodology is a technique employed in agricultural research that involves the integration of multiple models through the use of a meta-model. This meta-model is trained by taking the average of the output generated by the learned features from the base models. Bagging, also known as bootstrap aggregating, can be considered as a variant of the model averaging approach in the field of agricultural research. The principal objective of our conducted research endeavor is to train and optimize an ensemble CNN model for predicting diseases in cotton leaves with high accuracies. To achieve the desired objective, we extract images of cotton plant leaves from the plant village dataset. A comprehensive dataset comprising 1,786 images encompassing four distinct categories of cotton plant leaves has been curated. The leaves were classified into four distinct categories: those exhibiting optimal health and those displaying symptoms of one of the three identified diseases, namely 'Bacterial Blight', 'Curl Virus', and 'Fusarium Wilt' [26]. Figure 2 displays the visual representations of the four distinct categories of leaves.

The number of images across different categories in our dataset is presented in Table 1. The entire collection of images has been partitioned into two distinct subsets, namely the training and the testing. Upon partitioning the dataset into train and test subsets, we have observed the distribution of category-wise images in both sets, as depicted in Table 1. Figure 3 depicts a comprehensive workflow model illustrating the process of detecting cotton leaves disease, starting from the extraction of data sets and concluding with the identification of the disease.

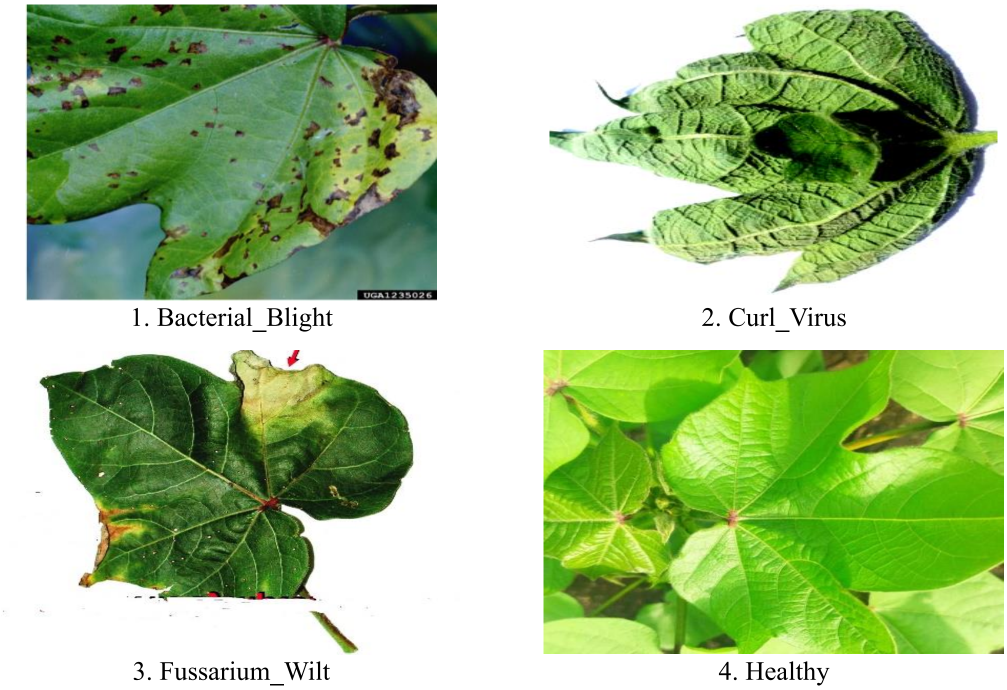


Figure 2. Cotton leaves appearances in different categories

Table 1. Cotton leaves categories in dataset with train and test set ratios

| Disease Name | Train | Test | Total |
|---|---|---|---|
| Bacterial_Blight | 434 | 90 | 524 |
| Curl_Virus | 334 | 84 | 418 |
| Fussarium_Wilt | 335 | 84 | 419 |
| Healthy | 340 | 85 | 425 |
| Total | 1,443 | 343 | 1,786 |

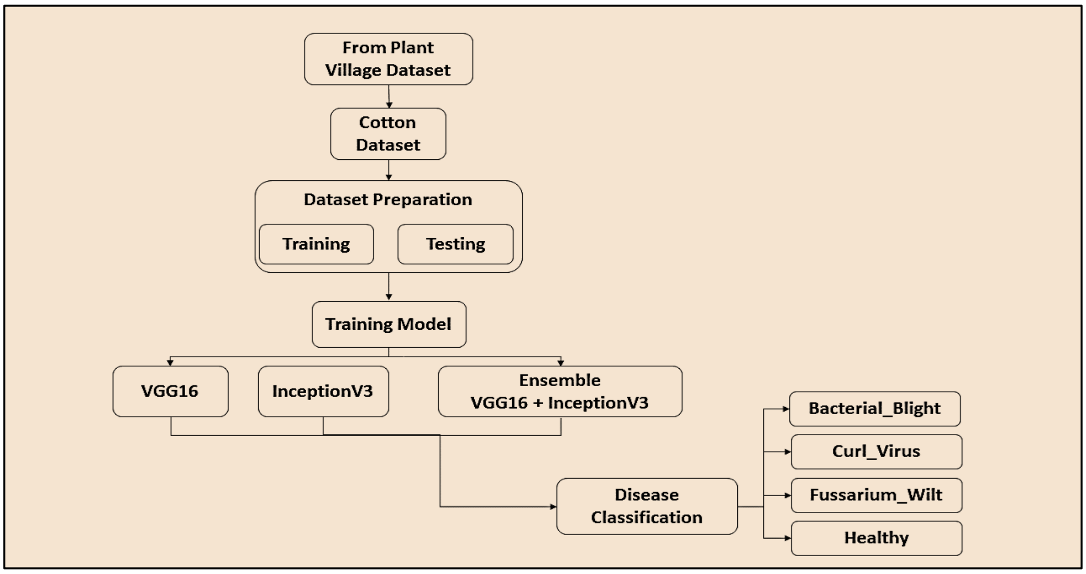


Figure 3. Work flow diagram for cotton leaves disease prediction

Upon extracting the necessary cotton images from the plant image dataset, we proceeded to partition the images into separate train and test sets. Subsequently, we conducted individual training sessions for the selected pretrained models, namely Inception V3 and VGG 16. Additionally, we also generated an ensemble model to further enhance our research findings. The findings from the classification process are subsequently aggregated for all three models.

## 3. RESULTS AND DISCUSSION

Pretrained models and ensemble model are trained and tested using Tensorflow and Keras frameworks of Python. System configuration used while experimentation is shown in Table 2. The initial training of all three CNN models is conducted using the Adam optimizer, employing learning rates of 0.001 and 0.0001. Results were acquired for epochs spanning from 5 to 20, inclusive, with intervals of 5. In order to optimize the performance of the cotton leaves dataset, a series of experiments were performed to quantify the training-testing accuracies and loss. These experiments involved varying the learning rates and epochs, with the aim of fine-tuning these specific parameters. The obtained results are shown in Tables 3 to 6. Table 3 presents the outcomes obtained from the implementation of the VGG 16 model, whereas Table 4 displays the results obtained through the utilization of the Inception V3 pretrained model on the cotton leaves dataset. The results indicate that the maximum accuracies for both training and testing, as well as the lowest losses for training and testing, are achieved when using a learning rate of 0.0001 over a period of 20 epochs. However, the greatest reported training accuracy for Inception V3 was 0.9642, surpassing the highest reported accuracy of VGG16. The testing accuracy for Inception V3 is 0.8746, surpassing the testing accuracy of VGG16.

Table 2. Employed system configuration for result genearation

| Hardware configuration | Type |
|---|---|
| Backend | Tensorflow and Keras |
| RAM | 16.00 GB |
| GPU | NVIDIA Quadro GP100, 3584 CUDA Cores |
| Operating system | Linux based Centos7 |
| Memory | 96 GB ECC (6 GB * 16), DDR4 2666 MHz, RAM in balanced configuration |

Table 3. Training and testing accuracies of VGG 16 model on cotton leaves dataset

| Learning rate | Epochs | Accuracy | | Loss | |
|---|---|---|---|---|---|
| | | Training | Testing | Training | Testing |
| 0.001 | 5 | 0.9189 | 0.8717 | 0.2281 | 0.3449 |
| | 10 | 0.9453 | 0.8367 | 0.1634 | 0.3974 |
| | 15 | 0.9349 | 0.8688 | 0.1691 | 0.3558 |
| | 20 | 0.9302 | 0.8592 | 0.0841 | 0.2911 |
| 0.0001 | 5 | 0.8413 | 0.8484 | 0.5373 | 0.5555 |
| | 10 | 0.8905 | 0.8717 | 0.3752 | 0.4356 |
| | 15 | 0.9189 | 0.8776 | 0.2982 | 0.3815 |
| | 20 | 0.9407 | 0.8659 | 0.2608 | 0.3766 |

Table 4. Training and testing accuracies of inception v3 model on cotton leaves dataset

| Learning rate | Epochs | Accuracy | | Loss | |
|---|---|---|---|---|---|
| | | Training | Testing | Training | Testing |
| 0.001 | 5 | 0.8995 | 0.8717 | 0.5051 | 0.5626 |
| | 10 | 0.9238 | 0.8484 | 0.5124 | 1.2486 |
| | 15 | 0.9023 | 0.7493 | 1.3717 | 4.6942 |
| | 20 | 0.9529 | 0.8980 | 0.5060 | 1.0564 |
| 0.0001 | 5 | 0.8552 | 0.8076 | 0.5144 | 0.5445 |
| | 10 | 0.8905 | 0.8338 | 0.3711 | 0.4635 |
| | 15 | 0.9120 | 0.8688 | 0.3022 | 0.3960 |
| | 20 | 0.9642 | 0.8746 | 0.2505 | 0.3839 |

Table 5. Training and testing accuracies and loss of ensemble model on cotton leaves dataset

| Learning rate and optimizer | Epochs | Accuracy | | Loss | |
|---|---|---|---|---|---|
| | | Training | Testing | Training | Testing |
| | 5 | 0.9757 | 0.9096 | 0.1291 | 0.2960 |
| 0.0001 | 10 | 0.9730 | 0.9184 | 0.1277 | 0.2748 |
| | 15 | 0.9806 | 0.9155 | 0.1124 | 0.2720 |
| Adam optimizer | 20 | 0.9813 | 0.8892 | 0.1001 | 0.2969 |

Table 6. Accuracies and loss for three CNN models at 0.0001 learning rate, Adam optimizer, 20 epochs

| Model | Accuracy | | Loss | |
|---|---|---|---|---|
| | Training | Testing | Training | Testing |
| VGG16 | 0.9407 | 0.8659 | 0.2608 | 0.3766 |
| InceptionV3 | 0.9642 | 0.8746 | 0.2505 | 0.3839 |
| VGG16+InceptionV3 | 0.9813 | 0.8892 | 0.1001 | 0.2973 |

Given that both pretrained models demonstrate higher accuracies when with a 0.0001 learning rate, therefore the ensemble model was executed with a learning rate of 0.0001. Table 5 presents the outcomes of the proposed ensemble model's training-testing accuracies and loss results. The model was trained using the Adam optimizer, with epochs ranging from 5 to 20. The observation reveals that the ensemble, being a meta-model, enhances parameter learning, resulting in better training and testing accuracies of 0.9806 and 0.8892 respectively after 20 epochs. This improvement is in comparison to the accuracies reported by the individual base models, VGG 16 and Inception V3. Additionally, it resulted in a decrease in the reported losses of both the base models. Table 6 presents a summary of the outcomes obtained from the ensemble model, VGG16, and Inception V3 model. These models were trained using a learning rate of 0.0001 for 20 epochs and Adam optimizer. Figures 4 depict the comparison study through the utilization of a bar graph. Figure 4(a) and 4(b) depicts the accuracy and loss comparative bar graph.

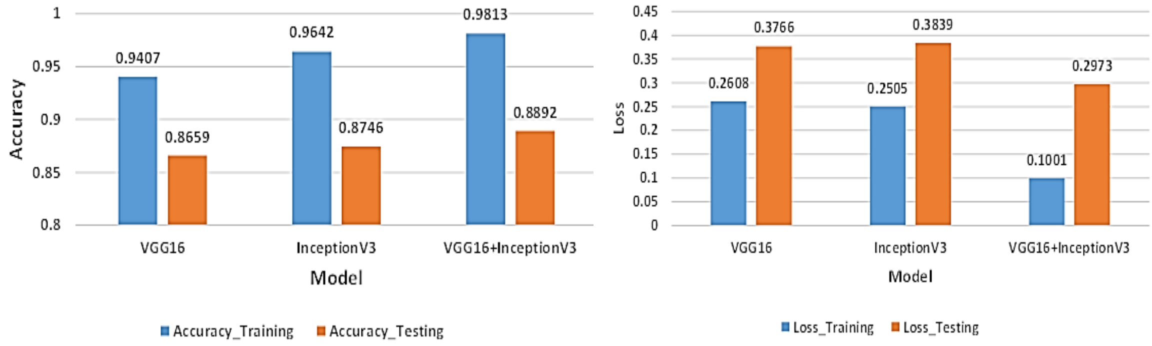


Figure 4. Training and testing (a) accuracy and (b) loss comparative bar graphs

### 3.1. Optimizer tuning results for ensemble CNN model

The ensemble model showed better results when the learning rate parameter was set to 0.0001 at 20 epochs. However, Adam optimizer was used in the aforementioned studies. As a result, additional testing to adjust the optimizer hyper-parameter is carried out using the SGD and RMSprop optimizers, while maintaining a learning rate of 0.0001. Table 7 lists the results of this experimental investigation. The training-testing accuracy results of the ensemble model were significantly enhanced by the SGD optimizer outcomes. It also decreased the losses seen during ensemble model training.

Table 7. Accuracies and loss results of ensemble CNN using different optimizers at 0.0001 learning rate

| Optimizer and learning rate | Epochs | Training | | Testing | |
|---|---|---|---|---|---|
| | | Accuracy | Loss | Accuracy | Loss |
| SGD | 5 | 0.9841 | 0.9841 | 0.9475 | 0.2435 |
| Learning rate=0.0001 | 10 | 0.9806 | 0.1388 | 0.9446 | 0.2453 |
| | 15 | 0.9792 | 0.1396 | 0.9446 | 0.2446 |
| | 20 | 0.9848 | 0.1341 | 0.9504 | 0.2424 |
| RMSprop | 5 | 0.2786 | 0.5812 | 0.2624 | 0.7695 |
| Learning rate=0.0001 | 10 | 0.2737 | 0.5731 | 0.2595 | 0.7804 |
| | 15 | 0.2772 | 0.5816 | 0.2624 | 0.7626 |
| | 20 | 0.2661 | 0.5748 | 0.2595 | 0.777 |
| Adam | 5 | 0.9757 | 0.1291 | 0.9096 | 0.2960 |
| Learning rate=0.0001 | 10 | 0.9730 | 0.1277 | 0.9184 | 0.2748 |
| | 15 | 0.9806 | 0.1124 | 0.9155 | 0.2720 |
| | 20 | 0.9813 | 0.1001 | 0.8892 | 0.2973 |

## 4. CONCLUSION

This paper presented an ensemble CNN model for cotton leaves disease detection. The experimental findings have demonstrated notable enhancements in the performance of the ensemble model when utilizing specific hyper-parameter values specific to cotton plant leaves dataset. A learning rate of ‘0.0001’ with ‘SGD’ optimizer, combined with a 20 training epochs, have yielded favorable outcomes in the considered dataset. Therefore, it is evident that the identification of diseases affecting cotton leaves can be significantly improved by employing an ensemble model that has been fine-tuned with optimal hyper-parameter values as suggested in this paper. This advancement in disease detection methodology holds great potential for benefiting all individuals and organizations involved in the agriculture and cotton industry. In order to further advance our research, we aim to augment the dataset by procuring real-time imagery of cotton plants encompassing a broader range of disease categories. This will enable us to explore a wider spectrum of disease classes and conduct more comprehensive experiments. A mobile application specifically designed for cotton farmers could be developed, focusing on utilizing a trained ensemble model to provide real-time predictions of cotton leaves diseases.

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