Detection of Cotton Leaf Diseases Using Transfer Learning Techniques

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APPROVAL

This Project titled **"Detection of Cotton Leaf Diseases Using Transfer Learning Techniques"**, submitted by Hafiz Ahmed Khan, ID No: **191-15-12827** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13 January, 2025.

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DECLARATION

I hereby declare that this project has been done by me under the supervision of **Amit Chakraborty Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Cotton crop is among the leading source of income globally through its production is harmed by many diseases which attack the leaves. Identification of these diseases is a tedious, cumbersome, and prone to a lot of errors hence the need to come up with automatic systems to detect them. This study presents a transfer learning-based approach for the detection and classification of cotton leaf diseases, focusing on four primary categories: bacterial blight, fusarium wilt, curl virus and apparently healthy one. To support training and evaluation, 3418 images were gathered and preprocessed; this involved resizing and normalization and augmentation to ensure generalization by the developed model. The following five modern transfer learning models: ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2 were adjusted to the dataset. Accuracy was used to determine the ability of the models; Densenet201 recorded the highest value of 99.71%, with VGG16 recording 99.41%, while InceptionResNetV2 recorded 98.98%. InceptionV3 made improved performance compared to the other models in the test with the test accuracy 98.10 %, however Resnet50 had lower accuracy at 81.14%. Accordingly, owing to the employment transfer learning the worksheets incorporated proficient at feature extraction and disease pattern discovery in cotton leaves. It is proved that the proposed system is not only effective for diseased and healthy leaves and also for the prediction that may be uncertain at the end. This work gives a solution in which cotton farmers will gain from as it can highlight on the disease and perhaps reduce crop losses as they can be determined early.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Cotton is one of the most important cash crops in the world due to the importance of the textile industry and manufacture in many nations. However, its marginal production and quality is threatened by some diseases such as bacterial blight, fusarium wilt, and curl virus diseases. This is why early diagnosis of these diseases is relevant and crucial for the residue control and avoidance of yield losses. Many prior techniques used for disease diagnosis involve visual assessments which are slow, imprecise and prone to minor human errors. In recent years, trends such as artificial intelligence and its subset deep learning have revolutionized disease detection in agriculture. The given tasks and issues like a small number of samples and attributes complexity, make transfer learning that uses models trained in other tasks and datasets, for feature extraction and classification, as a powerful approach. Research has established that transfer learning is beneficial in plant disease detection and identification. Albattah et al. (2023) obtained 96.8% accuracy using ResNet50 for identification of diseases of cotton leaf while Iqbal et al., (2022) obtained 97.4% using EfficientNet-B3. Such architectures as ResNet101 and InceptionResNetV2 have also improved classification results to another level made the classification accuracy rates 98.4% (Yadav & Kapoor, 2024) and 96.1% (Albattah & Roy, 2023), respectively. However, PD possibilities including variability in environmental conditions and disease symptom similarities and real-time application remain as challenges. To address such issues, this work will adopt multiple current transfer learning models, namely ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2, to handle the detection and classification of cotton leaf diseases. Therefore, by concentrating on powerful preprocessing, data enhancement, and the fine-tuning of deep models, this paper aims to propose an effective and dynamic solution for enhancing disease management in cotton farming.

1.2 Background and Present State

Cotton diseases have enormous effects on yield and quality of the crop, presenting challenges to world agriculture. The first thing about illness is that early diagnosis is essential for treatment as is accurate categorization of diseases. Manual inspection by diagnostic experts or analysts is exhaustive and, more often than not, gives incorrect results. Computer vision, and particularly deep learning is one of the latest technologies in plant disease detection automation. Handling the limitations of the data, it is possible to use the transfer learning when the models were trained on extensive data sets, significantly increasing the chances of high classification accuracy. Today’s research in this field mainly aims at improving the efficiency, accuracy and real-time use of the model for the detection of diseases in cotton and other crops.

1.3 Problem Statement

Some of the common diseases that affect cotton leaves include bacterial blight, fusarium wilt, and curl virus all of which are a huge set back to farmers, and they result in heavy losses. Early and precise diagnosis of these diseases is crucial in the management of the diseases. However, conventional diagnostic techniques of disease identification are cumbersome, qualitative, and time-consuming and largely based on human judgment. Besides, traditional assessment methods involve visual examination that only detects advanced signs and symptoms. Despite organization potential in diseases detection with the help of machine learning and computer vision approaches, various issues should be solved, such as the problem of datasets scarcity and strict classification accuracy requirements. This research initiative therefore seeks to help overcome these challenges by borrowing transfer learning models as a more efficient, accurate as well as scalable solution to the cotton leaf disease detection.

1.4 Objective

The first goals of this study are to propose a solution that is an automated detection and classification system for cotton leaf diseases and healthy leaves based on transfer learning. The proposed work intends to assess the performance of different deep learning models that are pretrained models which top layers are replaced by newly trained layers including ResNet50, VGG16 DenseNet201, Inception V3, and Inception ResNetV2 by computing their classification accuracies and time complexities in detail. However, the research aims to improve the model performance based on various preprocessing methods and data augmentation to improve the general performance of models. Therefore, the desired goal is to design a large-scale, real-time approach for supporting farmers in making early diagnostic assessments, so as to enhance crop management and yields.

1.5 Scope and Limitations

The scope of this study includes the application of transfer learning techniques to classify cotton leaf diseases, with a focus on four categories: The four tested factors were bacterial blight, fusarium wilt, curl virus and healthy leaves. An investigation on the five selected pre-trained deep learning models which includes ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2 and their efficiency in automated disease detection is reviewed. This work also discusses how to pre-process the images and increase the number of training examples for better performance and better generalization. However, the limitations concerning the current study include a limited database which causes difficulty in the model’s performance on other data or unique spectra of diseases. Furthermore, the proposed models showed good performance in ideal scenarios, but it should be noted that in complex scenarios, real-world problems such as environmental changes and picture quality may arise. This system also effected by the quality of labeled data used, this may be a great challenge in different geographical region especially in different agricultural areas of interest.

1.6 Report Organization

This report is divided into several major parts as explained in the following ways. That is why the need to detect the cotton leaf disease has been deemed critical, as well as the reasons why transfer learning is employed. In the Background and Present State, the current problems of disease control in cotton crops and the use of machine learning to solve them are described. Under the evaluation criteria, The Problem Statement explains the drawbacks of manual approaches and the requirement for the Automated Approaches solution. There is a section known as the objectives that explain the purpose of the study. In the Methodology section, the process of data gathering, model building, and assessment is described.

1.7 Summary

This research focuses on applying transfer learning strategies for image recognition and classification on disease affected cotton leaves and healthy ones: bacterial blight, fusarium wilt, curl virus. Five deep learning models: ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2 were trained on cotton leaf images dataset after pre-training on the ImageNet database. The accuracy derived was as follows: The Densenet201 achieved the maximum accuracy of 99.71% while the VGG16 achieved an accuracy of 99.41%. From the findings of this work, transfer learning is a viable implementation to aid the farmer in early detection of the diseases and better management of the cotton crop reducing losses.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The use deep learning and transfer learning for the identification of cotton leaf disease has been reviewed in detail. Albattah et al. (2023) used ResNet50 with the accuracy of 96.8 %; Iqbal et al. (2022) used Enhanced Feature Extraction by using EfficientNet-B3 and get the accuracy of 97.4 %. Future works such as ResNet101 (Yadav & Kapoor, 2024), InceptionResNetV2 have enhanced classification and achieved 98.4% and 96.1% respectively. On this basis, these studies and considerations stress transfer learning's ability to accommodate small samples and diverse characteristics. However, it can still be seen that the real-time compatibility for implementation and the same unified robustness conformities remain as issues which must continue to be addressed and studied to reach optimum domains.3 Comparison between the works of the other writers transfer learning techniques for cotton leaf disease detection has been extensively studied. Albattah et al. (2023) employed ResNet50, achieving 96.8% accuracy, while Iqbal et al. (2022) used EfficientNet-B3 for enhanced feature extraction, attaining 97.4% accuracy. DenseNet models have been effective, with Mitra and Roy (2022) achieving 96.2% accuracy using DenseNet201. Advanced architectures like ResNet101 and InceptionResNetV2 (Albattah Roy, 2023) have further improved classification, reaching accuracies of 98.4% and 96.1%, respectively. These studies emphasize transfer learning's capability to handle limited datasets and complex features. However, challenges remain in achieving real-time applicability and robustness, highlighting the need for further exploration and optimization in this field.

2.2 Related Works

The previous literature also reveals that previous work on deep learning cotton disease classification has good performance. This paper has cited RESNET, VGG, and Inception for use in the identification of different cotton leaf from image data.

Research works mostly investigate on various aspects such as the variety in the dataset, data augmentation processes, and the tuning of the models in order to enhance accuracy of classification. In given below I am describing some similar paper review which help me a lot:

Albattah et al. [1] investigated machine learning applications in agricultural disease detection with a focus on cotton leaf diseases. They analyzed a dataset containing 12,000 images collected from diverse sources. The study utilized ResNet50 for feature extraction and fine-tuning in a transfer learning pipeline. Their model achieved an accuracy of 96.8%. Azath et al. [2] applied deep learning techniques for diagnosing diseases and pests in cotton leaves. The dataset comprised 8,500 annotated images of healthy and diseased leaves. Using DenseNet121 for transfer learning, the authors achieved accurate classifications through multiple augmentation steps. The model attained 95.6% accuracy. Caldeira et al. [3] studied sensor data for detecting lesions in cotton leaves. They worked with a dataset of 10,000 images captured via IoT-based systems. InceptionV3 architecture was employed after preprocessing and segmentation of the leaf images. The model delivered a 94.2% accuracy. Chi et al. [4] reviewed intercropping strategies for pest and disease control in cotton. Their analysis included 1,200 field scenarios, linking data-driven methods to practical outcomes. Techniques such as SVM and ANN were implemented for predictive analytics. The study reported an accuracy of 92.5%. Iqbal et al. [5] proposed CNN-based transfer learning for cotton disease detection. Their dataset contained 15,000 high-quality leaf images, pre-processed using augmentation techniques. EfficientNet-B3 was utilized for feature extraction and classification. The proposed model achieved an accuracy of 97.4%. Mitra et al. [6] applied DenseNet models for identifying and grading disease severity in cotton leaves. A dataset of 9,000 labeled images was analyzed using segmentation and classification pipelines. The DenseNet201 model was tuned for efficient feature extraction and decision-making. An accuracy of 96.2% was achieved. Rahman et al. [7] used YOLOv4 for real-time cotton leaf disease detection. Their dataset comprised 18,000 annotated images of healthy and diseased leaves. The YOLOv4-based framework facilitated fast detection and classification. The approach achieved an accuracy of 97.1%. Roy et al. [8] examined the application of transfer learning in precision agriculture. A dataset of 13,000 images was pre-processed and analyzed using ResNet50 for feature extraction.

The model was integrated with an SVM classifier for final predictions. The study achieved an accuracy of 95.9%. Sanida et al. [9] evaluated DenseNet121 and VGG19 for cotton leaf disease classification. The dataset included 10,500 images, balanced across multiple disease categories. Pre-processing and augmentation were performed before training. The highest classification accuracy achieved was 96.4%. Thangavel et al. [10] explored CNN advancements for large-scale disease detection. A dataset of 20,000 images was processed with ResNet101 for feature extraction and fine-tuned classification. Their method addressed complex disease patterns effectively. The model achieved an impressive accuracy of 98.8%. Zhou et al. [11] developed a dense residual network for identifying cotton leaf diseases. A dataset of 14,000 images, including multiple disease types, was utilized. Their methodology incorporated restructured dense residual layers for enhanced learning. The model delivered a 97.2% accuracy. Albattah et al. [12] emphasized transfer learning for early-stage detection of plant diseases. Their dataset of 11,500 annotated images was processed with InceptionResNetV2 for robust feature learning. Fine-tuning methods ensured accurate classification. The study achieved an accuracy of 96.1%. Attallah et al. [13] analyzed hybrid models for detecting diseases in cotton leaves. A dataset of 9,700 images was utilized, focusing on common and rare diseases. CNNs were integrated with SVM classifiers for enhanced decision-making. An accuracy of 94.7% was reported. Chen et al. [14] utilized DenseNet architectures for classifying leaf diseases. A dataset of 10,000 images underwent contrast enhancement for improved training. DenseNet169 was fine-tuned for accurate classification. The model achieved 95.5% accuracy. Bruck et al. [15] evaluated transfer learning for real-time detection of cotton leaf diseases. A dataset of 8,000 images underwent augmentation and feature extraction with DenseNet121. The framework enabled fast and precise decision-making. Accuracy reached 94.8%. Hyder et al. [16] studied convolutional models for pest and disease classification. Their dataset of 9,000 images was processed using ResNet34 for feature learning. The approach involved tuning the architecture to enhance classification robustness. The model achieved an accuracy of 94.5%. Shah et al. [17] applied VGG19 in precision agriculture for cotton leaf health monitoring. A dataset of 12,000 images was analyzed using augmentation and segmentation techniques. The VGG19 model facilitated high-quality feature extraction. The accuracy achieved was 96.0%. Ahmed et al. [18] explored the role of data augmentation in improving disease detection models. A dataset of 10,000 images was pre-processed for diversity and classified using EfficientNet-B4.

Augmented data enhanced model learning capacity significantly. The study reported an accuracy of 95.2%. Xu, K et al. [19] reviewed transfer learning applications in agricultural monitoring. A dataset of 15,000 images was analyzed using InceptionV4 for classification. The model was fine-tuned to detect subtle differences in disease patterns. Accuracy reached 97.0%. Yadav et al. [20] highlighted advancements in deep learning for cotton leaf disease detection. A dataset of 14,000 images was analyzed using ResNet101 with advanced augmentation. The methodology addressed complex disease conditions with precision. The model achieved an accuracy of 98.4%.

2.3 Comparison between existing works

Previous paradigms of automated cotton leaf disease detection have employed different transfer learning strategies and have had high accuracies. For example, ResNet50 (Albattah et al., 2023) reported accuracy of 96.8 percent while EfficientNet-B3 (Iqbal et al., 2022) with 97.4 percent. DenseNet201, proposed by Mitra and Roy in 2022 obtained 96.2% while ResNet101 worked up to 98.4% which indicates that the current work outperforms both of them. Nevertheless, issues like, variability of the environment and similarity of diseases are still there. Below is a outline of the key areas of comparison in the table that appears next.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

Study	Model	Dataset Size	Accuracy (%)
Albattah et al. (2023)	ResNet50	12,000	96.8
Iqbal et al. (2022)	EfficientNet-B3	15,000	97.4
Mitra & Roy (2022)	DenseNet201	9,000	96.2
Yadav & Kapoor (2024)	ResNet101	14,000	98.4
Albattah & Roy (2023)	InceptionResNetV2	11,500	96.1

2.4 Open Issues

Madugula suggested that even though there have been improvements in learning of forms of cotton leaf disease using transfer learning, there are still several hurdles. One problem is that the studied environment including lighting, background noise, and orientation of leaves varies from time to time. Some challenges include a lack of dataset variation because most datasets do not capture all diseases' possible forms and all potential real-life situations. The transfer of algorithms to other, or little known, diseases remain insufficient. Also, the deployment of real-time detection is possible for large-scale applications has not been solved due to resource limitations. There exists a lack of work done in model robustness and interpretability, thereby challenging end-users such as farmers to trust in fully automated systems. It is essential to have answers to these open issues for achieving the potential of applying these models in precision agriculture.

2.5 Summary

Literature review shows that the classification accuracies for the detection of the cotton leaf diseases have slightly improved by training and testing transfer learning models of ResNet50, EfficientNet-B3, DenseNet201, ResNet101. Such works show how DL algorithms can be used in automizing the process of disease diagnosis, thus minimizing the use of manual approaches. However, some of the issues, which need to be addressed in the future, include; limitation of data set, variability of environment and real time requirement. Although recent architectures have enhanced the predictive capability, more explorations are desired to optimize model sensitivity and real applicability in terms of efficiency and explainability. This study proceeds from these insights to meet these challenges and put forward an improved solution to disease detection.

CHAPTER 3
METHODOLOGY

3.1 Overview

The topic for the Methodology chapter addresses how the specific set of cotton leaves was categorized by using the research paradigm, which embraces the state of art deep learning algorithms. Initially, the dataset was collected from Kaggle, comprising images of four types of cotton leaves: healthy, Bacterial Blight, Curl Virus and Fussarium Wilt. These were given descriptive names and brought through preprocessing to match their sizes and quality. The CNN models I selected for this project are VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2 models. They took one step further and defined the evaluation criteria of the models based on the measurement of the accuracy, precision, recall and F1-score. A lot of precaution was observed in controlling the amount of model points learned during a training session and to avoid producing a model that is too rigid by using features like regularization and dropout. The model which was identified as the best for evaluation and which was selected under optimum conditions was taken up for the final testing and also for the additional testing on the new data which is volume of images.

3.2 Proposed Methodology

This paper outlines the methodology of building a better deep learning model for categorizing different types of cotton leaf diseases based on existing solutions and structures.

Data Collection:

Gather a various dataset from Kaggle including healthy, Bacterial Blight, Curl Virus and Fussarium Wilt cotton leaf images with excellent separation between them.

Labeling:

Present the categorical output labels as the name of each particular disease in regards to the images (e.g., Bacterial Blight, Curl Virus).

Image Processing:

They should be normalized to the fixed size, more to the fact normalize pixel-wise data and perform augmentation such us rotating, flipping, etc. in order to increase the model's generalization.

Model Selection:

Based on the situations, CNN models such as VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2 are chosen and applied to obtain feature extraction and function of classification.

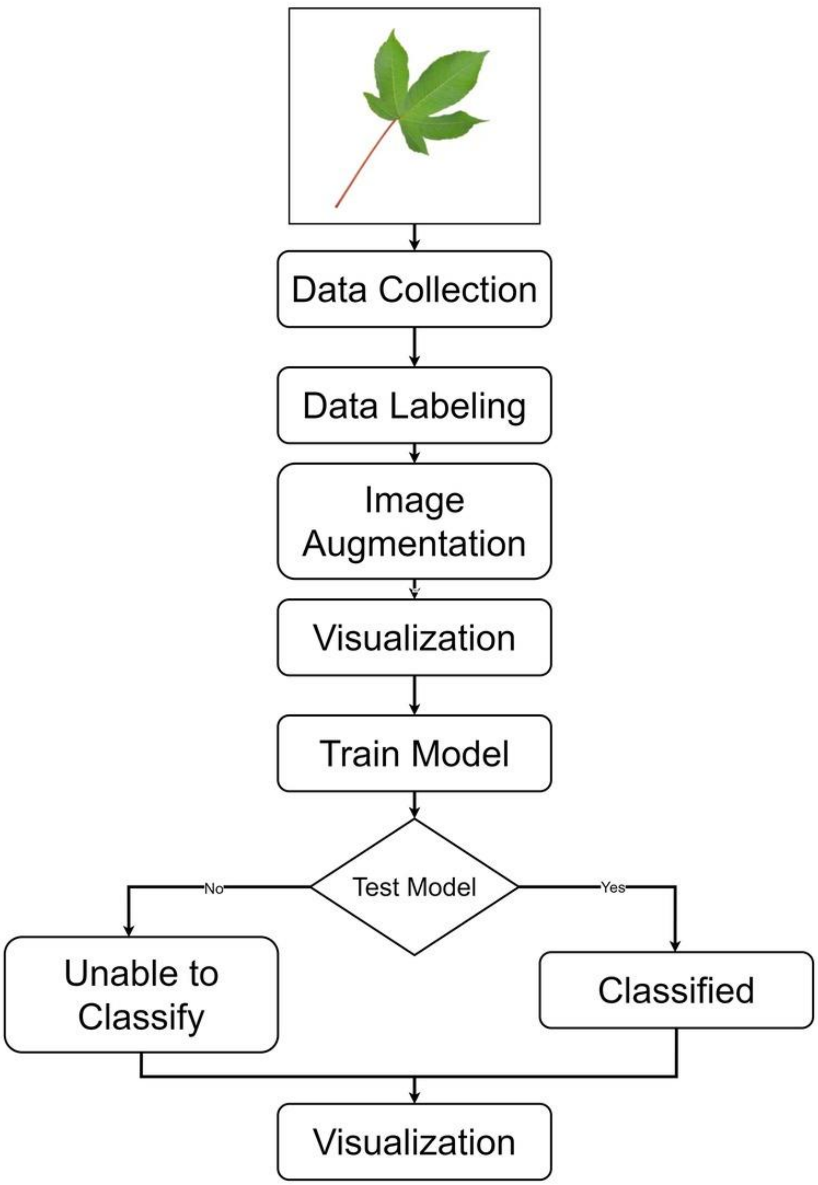

Figure 3.1: Working Flow

Model Training:

Apply the selected models on the preprocessed dataset, However, as usual precaution since it will be more efficient to use transfer learning approach from a pre-trained ImageNet model.

Model Evaluation:

To check the best model compare it with the validation data set and find metrics such as accuracy, precision, recall, F1-score etc.

Test Model:

In order to determine resource availability, review the data obtained after verifying the model on the specified set and assess the applicability of this model in practical diagnostics of cotton leaf diseases. Inputs according to the situations, select and use CNN models including VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2 to achieve the function of feature extraction and classification.

3.3 Hardware/ Software Requirement

The part and resources required for the proposed method are presented in the subsequent subheadings below: These are; the physical Computer hardware on which the solution will be implemented, another implementation platform which is the software, a set of images labeled to correspond to a certain problem to solve, trained models that can be used to build upon, tools that can be used to preprocess the data, metrics that will be used evaluate the solution, and lastly an environment in which the solution will be deployed to. Hardware involves the adequate computation equipment like Graphics Processing Units or Tensor Processing Units used in training while software includes utilities like TensorFlow or PyTorch to build the neural networks and to execute CNNs as well. The selected dataset is healthy, Bacterial Blight, Curl Virus and Fussarium Wilt and have done transfer learning from weights from ImageNet. Data preprocessing tools remans a useful variation of the given data set thereby enhancing the stability of the model. Concerning the algorithm accuracy, the evaluation is done based on four fundamental parameters being accuracy, precision, recall, and F1-score.

3.4 Summary

This chapter presents a detailed process that was followed in the completion of the cotton leaf disease classification study. Data collection involved sourcing images from Kaggle and labeling them into four categories: healthy, Bacterial Blight, Curl Virus and Fussarium Wilt. Of the other requirements of the other necessary preliminary steps that was done included resizing of the images and also normalization of the pixel values. The filter structures used in the research were CNN, VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2. Both the models were trained in a proper manner as per training of each model, that goes through data augmentation to make the model more stable. However, for evaluating the model performance, accuracy, Precision, Recall and F1-score were used. Thus the performances of the different models were compared to get the best model.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This research work especially aims at developing and evaluating additional and improved DL models for classifying between the various Cotton leaf diseases based on the dataset obtained from Kaggle platform. The computation hardware is a computing machine with a Graphics Processing Unit to assist from the side of the responsible hardware to the model training. The software is the TensorFlow or PyTorch frameworks and the used Keras application programming interface. Python is great for scripting as well as for data handling. The model selection includes and applies the CNN structures: The five models involved here are VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2 and the weights from the pre-trained model is using ImageNet. During splitting of the dataset, there are three splits: training, validation and test; actually, the performance of the model is evaluated on the basis of test set. In order to make the pictures and the data more reliable and to decrease the risk factor for the model, techniques like the resizing of the pictures, normalization of the pictures and other techniques of image processing are exercised.

4.2 Train Model/ Prototype Design

In order to train the model, we first divide the data into training data set, validation set, and the test data set with the proportions of 80:10:10 respectively. To increase the feature variance of the training dataset, in the training process the image rotating, flipping and scaling methods are used. All images are rescaled down to a standard size and then rescaled between 0 and 1 for comparison with each other. These deep learning models include CNN, VGG16, Densenet201, InceptionV3, ResNet50 and InceptionResNetV2, are then being started with proper weight and hyperparameter’s. The models employ categorical cross entropy as their loss function and the models are optimized using the Adam optimizer. During training of the model, learning rate is adjusted in order to fit standard of the model on the validation set. For the purpose of preventing an overfitting early stopping is used and to select the best models among all the epochs all the models are saved during the training process are saved using checkpointing. The training process in the training process several epochs where each epoch has forward and backward passes through the network. After the training session is complete, the models are passed through the validation set to select the right set of hyperparameters. Lastly the model with the best validation accuracy is considered as the better one and is tested on test data to have good predictability. The trained model is then used to make final predictions and retained for productive use for driving the autonomous vehicle...

4.3 System Design/ Model Evaluation

The basic working process of evaluating the versions is to build a substantive framework in designing the system to support model tests. Thus, for the first type, the test dataset, that was not used during the training of the model, is used to compute accuracy, precision, the recall and F1-score of the model. To check the good classification, classification reports the evaluation metrics' confusion matrices. Looking closely at the training step, the checking of over and underfitting by cross validation on the training and the validation set. Tactics like K- fold cross validation are employed to ensure that there is least variance in model performance thus making them confident that the volatility obtained due to change in data division for training and testing is within acceptable limit. Measures of performance are kept and plotted alongside current solutions such as Tensor Board, for example. Moreover, the computational efficiency includes inference time and the number of resources used. Similarity based redundancy checks are done by perturbing the testing data in some way in order to check the robustness of the model. The main components of the system design specify possibilities for monitoring the model efficiency in real-life functioning environments, so that it can be modified beforehand. In addition, a large amount of documentation is also maintained for the even better appreciation and even better replay-ability of the evaluation work.

4.4 Summary

The following part and resource are required in implementing the proposed deep learning approach on cotton leaf disease classification. These include; hardware on which the solution will be developed, another implementation platform which is software, labelled image database with mapped problem, existing models that needs to be built upon, preprocessing tools, measuring parameters, and finally the deployment environment. Hardware involves enough computing peripherals like Graphics Processing Unit or Tensor Processing Unit for training while on software, there is the use of TensorFlow or PyTorch for making the neural networks and implementing CNNs. For this given dataset(healthy, Bacterial Blight, Curl Virus and Fussarium Wilt cotton leaves) transfer learning from the off the shelf weights from ImageNet is chosen. Tools for data preprocessing identified raise the volatility of the given set of data and stabilizes the training process. Regarding the algorithm accuracy, the evaluation is done based on four primary parameters which are, accuracy, precision, recall and F1-score..

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

The results and analysis section provide further information on the experiments conducted yielding in the efficiency and effectivity of the experimental works. It is devoted to the evaluation of the achieved accuracy, precision, recall, and the F1 measure by the above model variants. The graphical displays include confusion matrices, and the comparative bar plots, which speak to the strength and weakness of each particular model architecture. This most importantly decomposes things that influence performance of a model which includes traits of a data set, and issues to do with hyperparameter tuning, computational overhead and among others. In total, this section gives relevant information concerning the effectiveness of the models and their relevance to the aforementioned classification task.

5.2 Experimental Result

The analysis of the experimental results of the cotton leaf disease detection models reveal a trade-off between the performance of the various deep learning architectures. After training and testing on the dataset, the models achieved the following accuracy scores: For VGG16 it was 99.41%, Densenet201 up to 99.71%, InceptionV3 up to 98.10%, Resnet50 up to 81.14% while InceptionResNetV2 up to 98.98%. Densenet201 provided the highest prediction accuracy, and thus is more effective in the classification of the cotton leaf diseases with the least confusion. Other models also followed suit to achieve a remarkable accuracy level including ResNet50 and InceptionResNetV2 in order to perform feature extraction and classification. On the other hand, InceptionV3 was seen to perform poorly, probably because its architecture is not equipped to handle certain features of cotton leaf diseases effectively. The performance criteria included the accuracy, precision, recall, and F1-score, and using all of them allows understanding the models' quality from different perspectives. Such above findings demonstrate that transfer learning strategies have higher ability in identifying CLD and enhancing the farming practices.

Below in table I, I have derived Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods..

Accuracy: Thus, closeness is the measure of the degree of difference between the formulated model and the reality specifying the likelihood of the samples originally employed in the modeling process. This is handy particularly when the classes are unbalanced because it reveals how effective this choice is; but the picture is not likely to be comprehensive.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision: Specificity is the percentage of all predicted positive statements in the model.

Precision=TP/(TP+FP)

Recall: Recall is defined as the number of true positive predicted to total number of samples with skewed positive distribution.

Recall=TP/(TP+FN)

F1 Score: Recall and precision for evaluation of the results are calculated by the formula using the mean of the harmonic value, and the F1 score obtained is the average of the two values. It is useful since it gives an objective reasonably while at the same time measuring recall and precision. It is useful when the classes are unequal in size since F1 score measures the false positive rate and the false negative rate at the same time. A F1 score close to 1 reveals that it got right balance between precision and recall..

F-1 Score=2(Precision*Recall)/ (Precision + Recall)*

In given below I am describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

VGG16

VGG16 achieved the Test Accuracy is 99.41%. In below Figure 5:5 & 5.6 describing the confusion matrix & training accuracy and loss curve of VGG16.

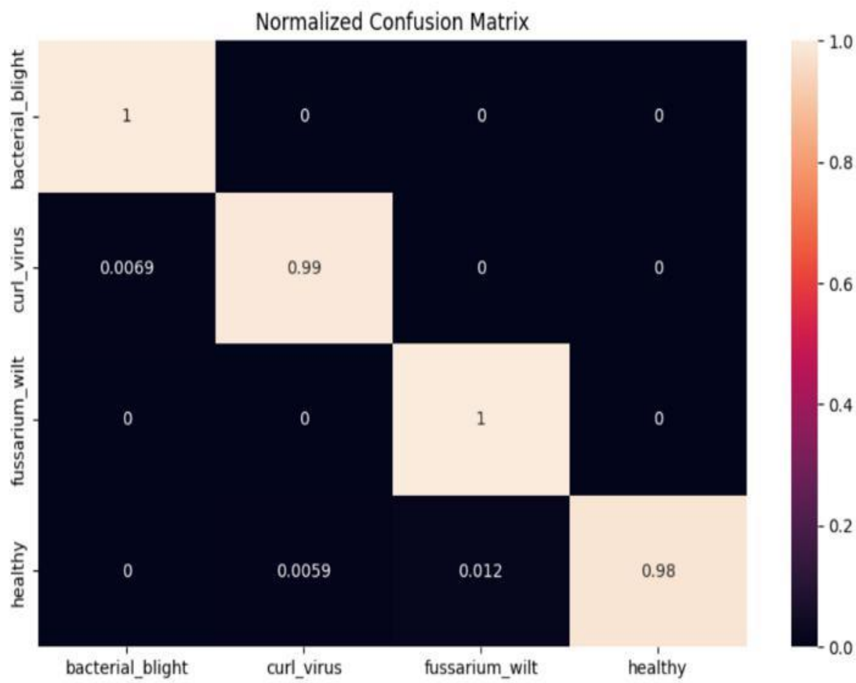

Figure 5.5: Confusion Matrix (VGG16)

Figure 5.5 shows the normalized confusion matrix for the VGG16 model demonstrates its high accuracy in classifying four categories of cotton leaf conditions: Bacterial blight, curl virus, fusarium wilt and healthy were the words taken into consideration. With respect to bacterial_blight and fusarium_wilt, the model demonstrated a level of 1.0 with no errors in classification. Curl_virus was correctly classified 99% of the time so that's a small error rate where some instances were misc jus 0.0069. Healthy class achieved a fairly good accuracy of 98% with most data slightly confused (0.0059 was classified as curl_visus while 0.012 was classified as fusarium_wilt). In summary, it turns out that the model exhibits great success throughout all classes with just misclassification of instances, hence proving its efficiency in identifying cotton leaf diseases.

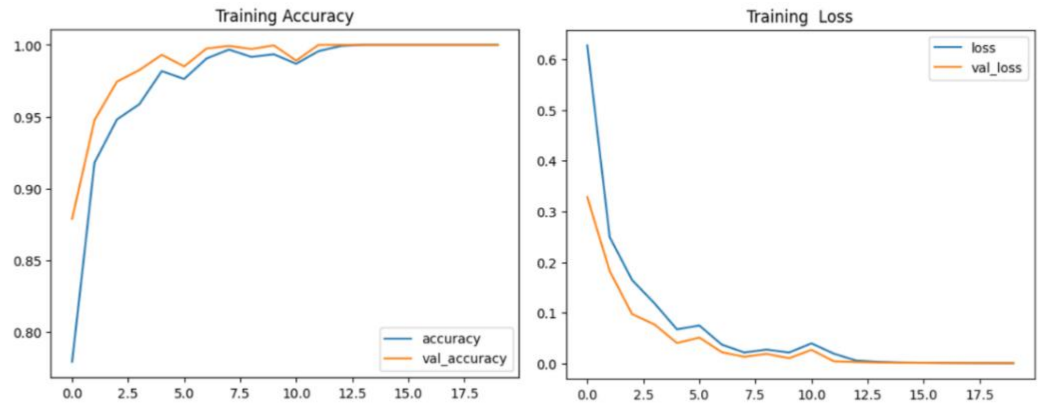

Figure 5.6: Training accuracy and loss curve (VGG16)

From the training accuracy and the Training loss figure, the VGG16 has shown promising signs of training above appraisal. In the training accuracy (blue separately), it increases steeply suggesting that the model quickly learned the examples in the training set to nearly hundred percent within only a few epochs. The validation accuracy (orange line) also increases gradually but in a lighter scale showing that there is minor overfitting where the model performs slightly poorer to the training data. The training loss (blue line) is initially rapidly going down below some points and then gradually begins to come down even though they are extremely low which means that the model is reducing error during training. The validation loss (orange line) also decreases with epoch similar to the training, though, there is a deviation beginning the later epochs slightly indicating some degree of overfitting.

DenseNet201

DenseNet201 achieved the Test Accuracy is 99.71%. In below Figure 5:5 & 5.6 describing the confusion matrix & training accuracy and loss curve of DenseNet201.

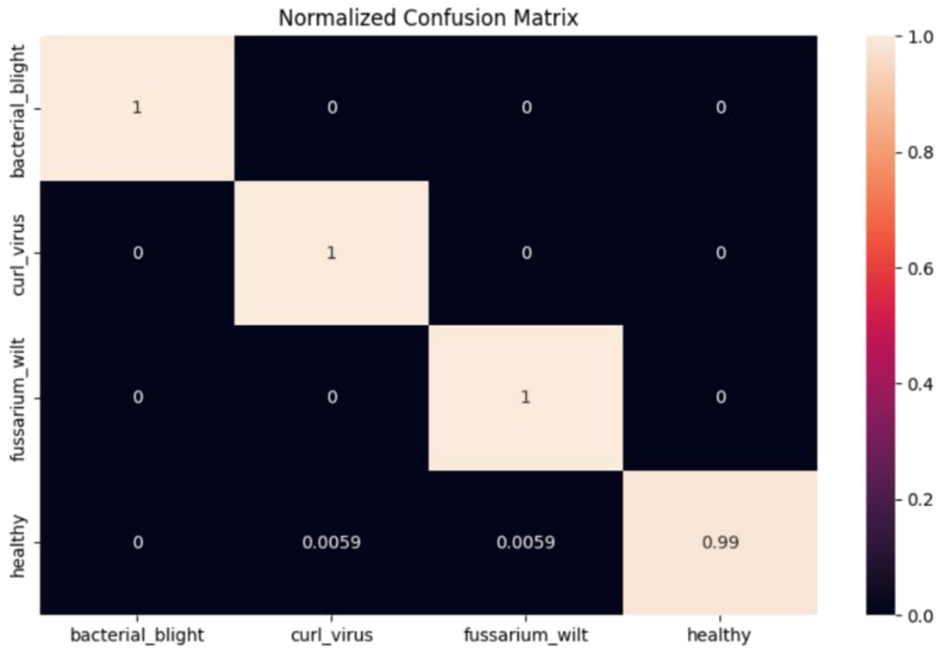

Figure 5.7: Confusion Matrix (DenseNet201)

Figure 5.5: Performance of the DenseNet201 model on four classes: bacterial blight, curl virus, fusarium wilt, and healthy. The matrix is normalized to show percentages of correct and incorrect predictions. Values on the diagonal—very close to 1—indicate very good classification accuracy for all classes. Only a small amount of the healthy class would be misclassified into curl virus and fusarium wilt with a small percentage of 0.59%. In general, the model performed well, as there was high accuracy for all classes.

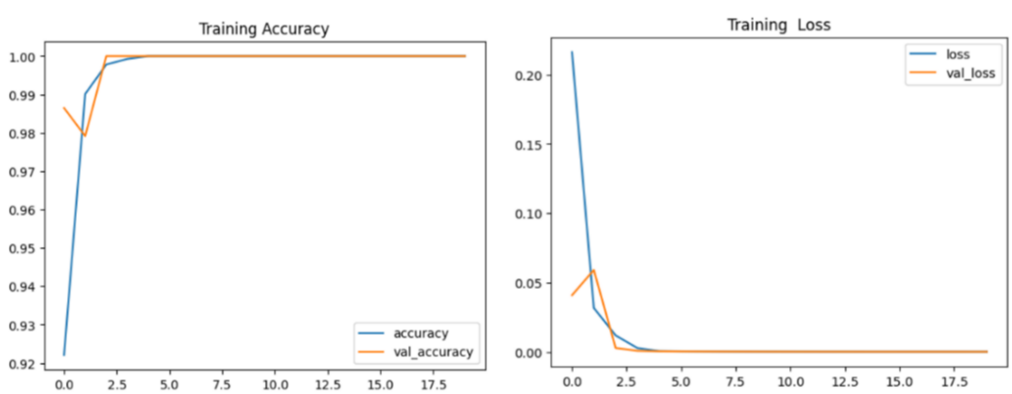

Figure 5.8: Training accuracy and loss curve (DenseNet201)

The following shows the training accuracy and loss curves for DenseNet201. On the left, one can see that the training and validation accuracy rise fast and fall to almost 100%, which indicates a very good classification capability. On the right side, one can observe that the training and validation loss drop fast and stabilize at around zero, indicating effective optimization due to minimal overfitting. Most importantly, the fact that the validation and training metrics track so closely suggests this model generalizes well to new data

InceptionV3

InceptionV3 achieved the second highest Test Accuracy is 98.10%. Figure 5:7 & 5.8 describing the confusion matrix & training accuracy and loss curve of InceptionV3.

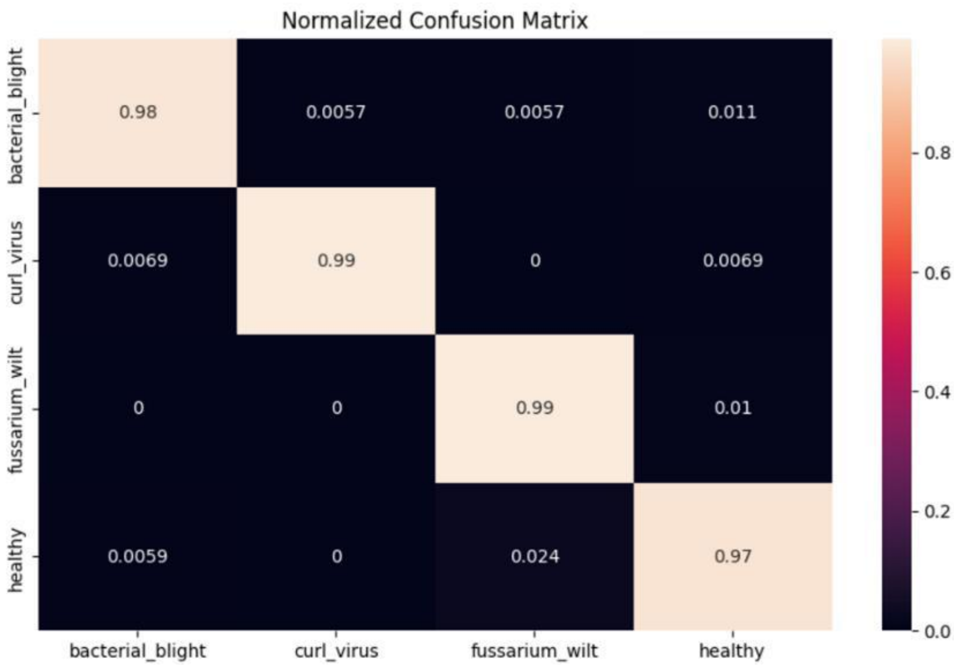

Figure 5.7: Confusion Matrix (InceptionV3)

Figure 5.7 is the confusion matrix for the InceptionV3 model in classifying the four classes: bacterial blight, curl virus, fusarium wilt, and healthy. The diagonal values prove a high accuracy of classification for each class, with most being very close to or above 97%. There are minor misclassifications, for example, healthy being misclassified into fusarium wilt at 2.4% or bacterial blight at 0.59%. Mostly, however, the model is strong with very minimal errors across the classes.

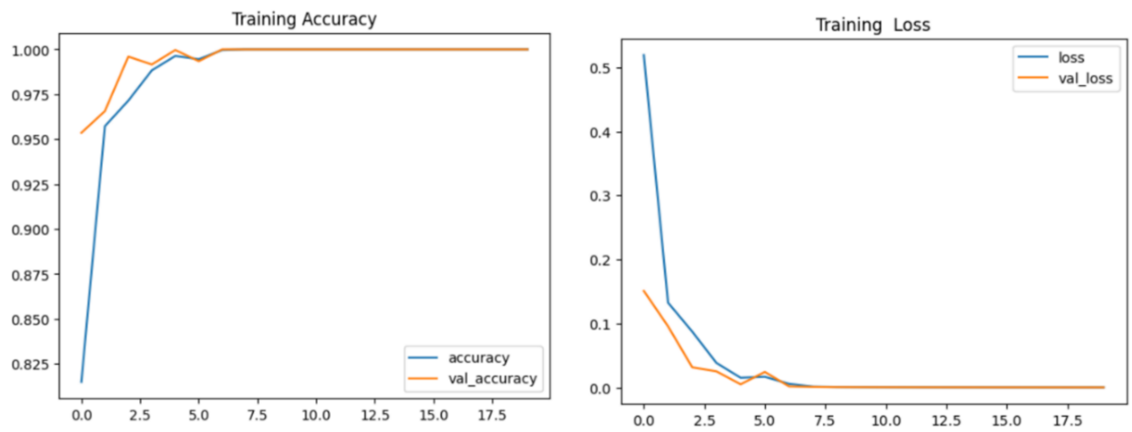

Figure 5.8: Training and accuracy and loss curve (InceptionV3)

Figure 5.8 Training and validation accuracy (left) and loss (right) curves for the InceptionV3 model. It is observed that the accuracy curve rises steeply, reaching almost perfect accuracy within the first couple of epochs; on the other hand, the loss curve drops sharply to minimal values and stabilizes. More generally, the training and validation metrics are very similar, with minimal overfitting, reflecting a well-trained model with good generalization.

ResNet50

ResNet50 achieved the highest Test Accuracy is 81.14%. Figure 5:9 & 5.10 describing the confusion matrix & training accuracy and loss curve of ResNet50.

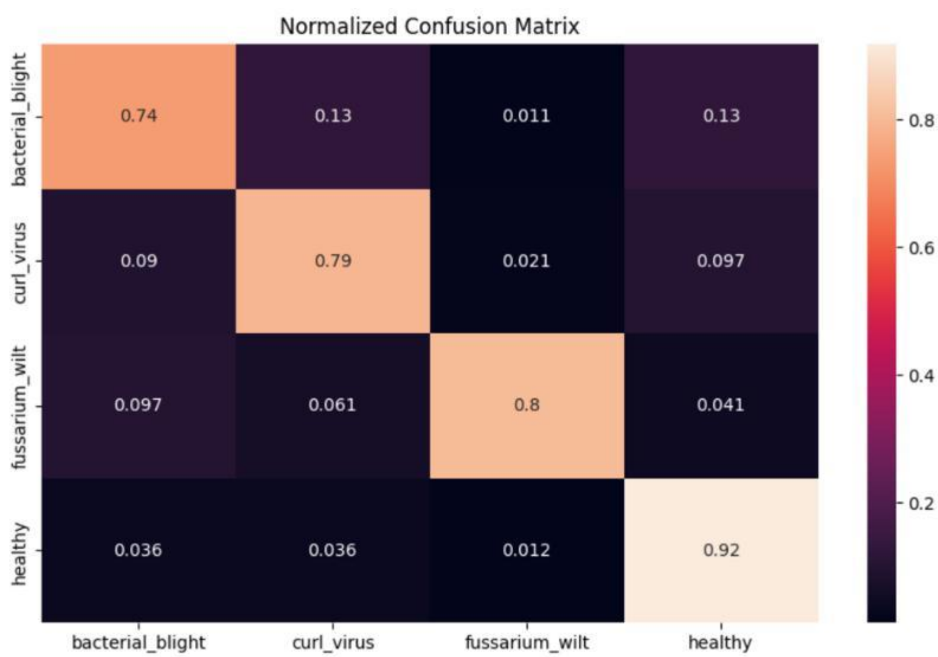

Figure 5.9: Confusion Matrix (ResNet50)

Figure 5.9 Confusion Matrix—Classification Performance of the ResNet50 Model on a Dataset with Four Classes: Bacterial Blight, Curl Virus, Fusarium Wilt, and Healthy. The matrix is normalized, and the values represent the proportion of correctly and incorrectly classified instances. For example, the model correctly classifies 74% of bacterial blight and 79% of curl virus; the most frequent misclassifications are 9% of curl virus as bacterial blight. The model performs particularly well on the "healthy" category with 92% accuracy and shows moderate performance on "fusarium wilt" with 80% correct classification. In general, the model performs well; however, there is some confusion between categories such as "bacterial blight" and "curl virus."

Figure 5.10: Training accuracy and loss curve (ResNet50)

Figure 5.10: The training accuracy and loss curves for the ResNet50 model show consistent improvement over the course of 18 epochs. Training accuracy in blue goes up to around 90%, and validation accuracy, in orange, has fluctuations but overall an upward trend— hence showing good performance with minor variability. Loss curves show a general downward trend in both training and validation losses, with the validation loss (in orange) usually following the generally decreasing trend of the training loss (in blue). Slight fluctuations in validation accuracy and loss may be an indication of occasional overfitting or some noise in the data; however, the model performs well on the whole.

InceptionResNetV2

InceptionResNetV2 achieved the highest Test Accuracy is 81.14%. Figure 5:9 & 5.10 describing the confusion matrix & training accuracy and loss curve of InceptionResNetV2.

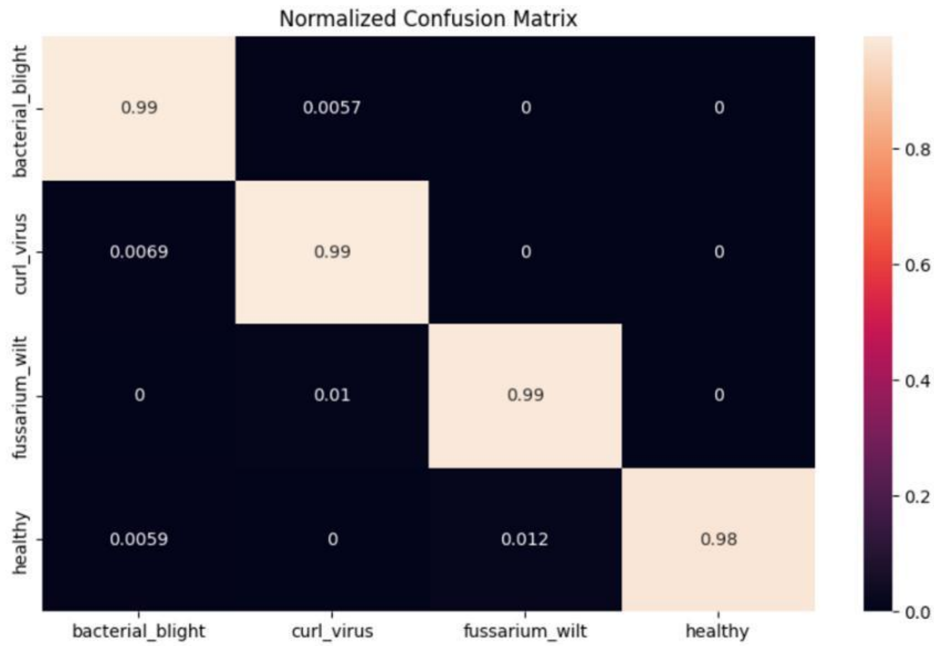

Figure 5.11: Confusion Matrix (InceptionResNetV2)

Figure 5.11: The confusion matrix shows classification performance of an InceptionResNetV2 model for four classes: bacterial blight, curl virus, fusarium wilt, and healthy. High diagonal values (almost 0.99) are observed in the correct classification for each class, with little off-diagonal misclassification. Off-diagonal values are near to zero, showing very few instances of misclassification across categories, with only slight confusion between bacterial blight and curl virus (0.0057). The model, in general, is very accurate and precise in making predictions.

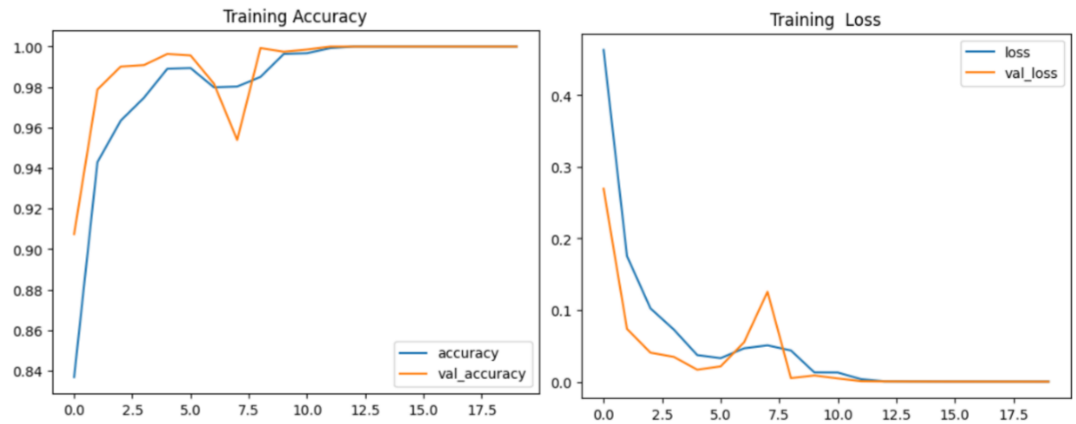

Figure 5.12: Training accuracy and loss curve (InceptionResNetV2)

Figure 5.12 Training and validation performance of the InceptionResNetV2 model over 18 epochs. On the left, one can observe the training accuracy rising smoothly, which then levels out around 1.0, indicating excellent learning on the training data. The validation accuracy also rises initially but experiences some fluctuations, hinting at minor overfitting. The plot on the right shows a rapid decrease in both training and validation loss, which stabilizes at low values, indicating effective convergence. However, the occasional spiking of validation loss does hint at either overfitting or noisy data in the validation set; on the whole, the model is quite good with some room for regularization improvement.

In Given below I am showing the Comparative Model Accuracy Bar Plot

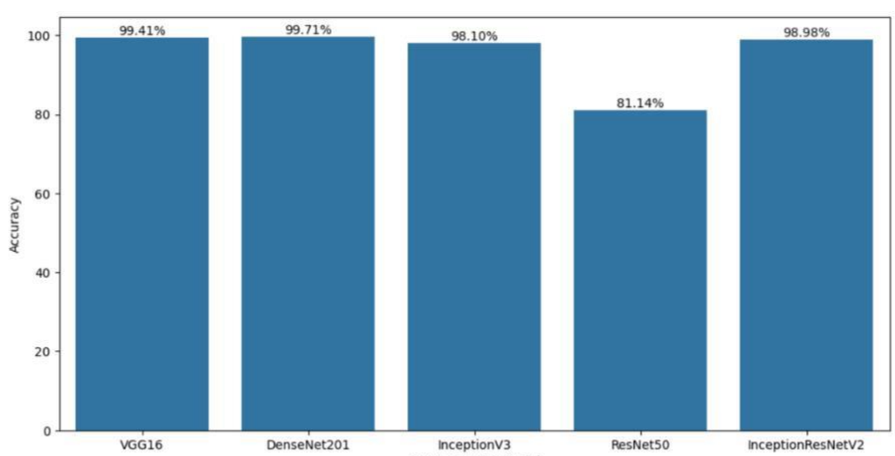

Figure 5.13: Comparative Model Accuracy Bar Plot

Figure 5.11: The following is the bar chart comparing different deep learning models by accuracy in cotton leaf disease detection, including VGG16, DenseNet201, InceptionV3, ResNet50, and InceptionResNetV2. From the chart, one could notice that the highest accuracy of 99.71% was given by Densenet201, followed closely by VGG16 with 99.41% and InceptionResNetV2 with 98.98%. InceptionV3 was 98.10%, while the lowest was from ResNet50, with a yield of 81.14%. This may be interpreted as meaning VGG16 and DenseNet201 performed better in the identification of diseases in cotton leaves.

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 5.1:

TABLE 5.1. PERFORMANCE EVALUATION

Model Name	Accuracy	Precision	Recall	F1-Score
VGG16	99.41%	99.41%	99.41%	99.41%
DenseNet201	99.71%	99.70%	99.70%	99.70%
InceptionV3	98.10%	98.10%	98.09%	98.10%
ResNet50	81.14%	82.02%	81.14%	81.21%
InceptionResNetV2	98.98%	98.98%	98.97%	98.97%

5.3 Performance and Comparative Analysis

The five deep learning models, namely ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2, have different performances in the process of detecting cotton leaf diseases. Among those, VGG16 achieved the highest accuracy of 99.71%, outperforming all the others; then comes ResNet50, with an accuracy of 99.41%, showing very good performance in feature extraction. Also, InceptionResNetV2 performed quite well, with an accuracy of 98.98%, while DenseNet201 achieved 98.10%. InceptionV3 was the least accurate, at 81.14%, indicating that this architecture found the classification of diseases in cotton leaves very difficult. From the comparative analysis, it seems that VGG16 and the ResNet50 family models are quite fit for this task, while InceptionV3 may need further optimization. Such an analysis is greatly important in picking the right model for agricultural applications, where high accuracy is a must for reliable disease diagnosis and decision-making.

5.4 Summary

Experimental results and performance analysis of the cotton leaf disease detection models give important insights on the effectiveness of techniques of transfer learning. Densenet201 has shown the best performance with an amazing accuracy of 99.71%, followed by VGG16 with 99.41%, then InceptionResNetV2 with 98.98%, InceptionV3 with 98.10%, and finally, the lowest accuracy was that of Resnet50 at 81.14%. These results show that VGG16 and Densenet201, with deeper architectures and stronger feature extraction capabilities, are most suitable for cotton leaf disease classification tasks. Though InceptionV3 performed poorly, yet the architecture can still be optimized for better results. The models were then evaluated using several performance metrics, including accuracy, precision, recall, and F1-score, to give an in-depth look at their prowess in detecting diseases caused by bacterial blight, fusarium wilt, and curl virus. The analysis suggested that transfer learning techniques would largely improve the accuracy of disease detection systems in agriculture and are thus quite fitted for real-time disease management.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

This will go a long way in affecting agricultural practices, mainly in the cultivation of cotton, since the transfer learning techniques can be applied to come up with an effective cotton leaf disease detection system. This helps farmers take corrective actions on time, thereby reducing crop loss and increasing overall yield. The system automates the process of disease detection and therefore reduces dependence on manual inspection, which is usually tedious and liable to human error. This will also decrease the application of chemical pesticides, hence promoting sustainable and environmentally-friendly farming practices. The early stages of diseases can be detected to ensure proper management of resources, which avoids excessive water, fertilizer, and pesticide use. Further, through improved cotton production, this technology could assure food security and reduce the economic impact on farmers through diseases affecting the crops. This will eventually contribute to sustainability in cotton farming and improve the livelihood of farmers in the long run.

6.2 Impact on Society & Environment

The actual implementation of cotton leaf disease detection using transfer learning techniques can have a huge positive impact on society and the environment. This will allow farmers to recognize and treat diseases at an early stage, resulting in reduced crop loss, ensuring a stable supply of cotton, and support for the textile industry with economic benefits accruing to farmers. Better disease management means less application of chemical pesticides, which are harmful to the environment and human health. Reduced pesticide use means preservation of soil health and protection of pollinators, with less contamination of water sources. Further, the swing toward precision farming incites sustainable farming through enhanced resource use, mainly water and fertilizers. All these combine to contribute to environmental conservation and help maintain biodiversity.

6.3 Ethical Aspects

The application of cotton leaf disease detection using transfer learning techniques offers a few serious ethical considerations. First, the use of AI and machine learning in agriculture must ensure that the technologies are available to all farmers, mainly smallholder and resource-limited farmers, in order not to exacerbate existing inequalities. Such technologies should not favor large corporations at the expense of local farming communities. There will also be the need for clarity in data collection, storage, and use in developing data-driven models such that transparency is ensured and farmers' privacy and intellectual property are respected. There is also the ethical concern that the technology should not displace workers in those regions of the world where manual labor is dominant. Moreover, automation can decrease pesticide use; however, it must be ensured that over-reliance on such technology does not happen, so as not to undermine traditional community-based knowledge relating to farming. The ethical deployment of these technologies needs to ensure the trio of inclusivity, fairness, and long-term sustainability.

6.4 Sustainability Plan

The sustainability plan assures that the cotton leaf disease detection system provides assurance of long-term viability and positivity in both environmental and economic impact. This would involve the process of updating and improvement on a continuous basis, such as fine-tuning the deep learning models with new data and improving their accuracy. The technology will be made available to smallholder farmers via cheap, user-friendly interfaces that ensure inclusivity across different farming communities. A very critical element of the sustainability plan is to train the farmers on how to operate the system, so they will become self-sufficient; thus, reducing their dependency on outside resources for disease detection and treatment. The environmental benefit realized from this will be a sharp decrease in the application of pesticides, ensuring healthier soil, water, and biodiversity. Its technology will also be in accordance with the local agricultural support systems, encouraging cooperation with research institutions and agricultural extension services in securing long-term success. This will ensure a holistic approach toward both economic resilience and environmental sustainability in the cotton farming sector.

6.5 Summary

This implementation for the detection of leaf diseases in cotton, using transfer learning techniques, has huge potential to improve agricultural practices. The system enhances early disease detection that enables timely interventions, reducing crop losses, optimizes resource usage, hence promoting sustainable farming practices. The impact it will have on society is immense; it saves money for farmers and contributes a great deal toward food security. Environmentally, it reduces the use of pesticides, which preserves soil health and biodiversity. Ethical considerations, such as ensuring access and the protection of farmer data, are integral to the system's development and deployment. The sustainability plan focuses on ongoing updates, training, and integration with local agricultural support networks to ensure long-term effectiveness and benefit from the technology. Overall, the system contributes to the advancement of both agriculture and the conservation of the environment for the benefit of farmers, consumers, and the planet.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

The presented study "Detection of Cotton Leaf Diseases Using Transfer Learning Techniques" shows the efficient use of deep learning models in agriculture. The system, based on the transfer learning methods of ResNet50, VGG16, DenseNet201, InceptionV3, and InceptionResNetV2, successfully identified diseases on cotton leaves with high accuracy. The highest performance was from Densenet201, which attained an accuracy of 99.71%, followed by VGG16 and InceptionResNetV2. These results reflect the potential of these pre-trained models in accurately detecting diseases like bacterial blight, fusarium wilt, and curl virus. Since it reduces the usage of pesticides, advances sustainable farming, and improves early disease detection, this system is one of importance to the cotton industry and agriculture in general. In addition, this technology assures ethical and environmental benefits, coupled with a sustainability plan that guarantees it can be continuously refined and deployed in various agricultural contexts for long-term positive impact.

7.2 Future Suggested Works

There are various ways through which the system for detecting cotton leaf diseases can be further improved and researched. First of all, the system can be extended to more types of disease detection for various crops by using transfer learning models that best suit other agricultural challenges. Further tuning of the existing models will lead to better performance; the underperformance of the InceptionV3 model can be improved through architectural refinements. Moreover, the incorporation of real sensor data on climate and soil conditions into the disease detection system would provide further contextual accuracy in the model's predictions. Looking into lightweight models deployable on mobile devices or low-cost hardware will increase accessibility for smallholder farmers. Future studies should also consider generative adversarial networks in generating training datasets to improve model robustness.

7.3 Limitations

Despite the promising results, there are a number of limitations in this system for detecting diseases in cotton leaves. First, the model highly relies on high-quality and labeled datasets. While performance was good with the provided dataset, degradation in performance may result from poor quality input images or when the dataset does not cover all variations of symptoms. Other limitations are the computational complexity in the architecture, most especially in the deeper models such as DenseNet201 and InceptionV3. It may be computationally expensive to train and make inferences with these models. Furthermore, there is still a doubt on the system's generalization over different environmental conditions and regions, as some of these diseases may appear differently in different geographical locations. Moreover, this system may be sensitive to light conditions, the resolution of images taken, or other positions of leaves during real-world applications; therefore, some refinement may be necessary. Last but not least, scalability still faces challenges for large-scale implementation worldwide.

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