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Sooty Mold Disease Detection on Cotton Leaves Using Deep Learning

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Abstract: Cotton growing in Pakistan, one of the key crops in both the agriculture and textile sectors, is facing serious problems related to diseases, such as Sooty Mold, which causes significant reductions in yield and quality. Traditional disease detection methods are recognized as inadequate; therefore, this research exploits Convolutional Neural Networks (CNNs), especially VGG-16 and Xception models, to automate and improve the accuracy of detecting Sooty Mold's disease in cotton leaves. This study utilized a dataset consisting of 695 training images and 251 validation images to demonstrate the ability of the models to distinguish between healthy and Sooty Mold-infected leaves with impressive accuracy. The VGG-16 model achieved a training accuracy of 99.43% and validation accuracy of 99.40%. The Xception model achieved a training accuracy of 99.6% and a validation accuracy of 99.55%, which were better than those of the VGG-16 model. In addition to theoretical model development, this research furthers its implementation into a practical solution through the development of an Android application. The development of this application, aimed at real-time detection of diseases, is a significant step forward in the process of merging technology and agriculture. Cotton crop growers are presented with a tool for the immediate action and management of the Sooty Mold. The implementation of deep learning models in a user-friendly mobile platform introduces a new method for precision agriculture and, with it, the possibility of transforming crop disease management practices. The success of these models, along with mobile technology, has set a new standard for agricultural innovation, thus contributing significantly to agroecological farming practices and the preservation of valuable cotton crops, not only in Pakistan but also in other countries.

Keywords: Sooty Mold; Cotton Leaves; Deep Learning; VGG-16; Xception.

1. Introduction

Cotton, an essential cash crop in Pakistan sometimes referred to as "White Gold," plays a key role in driving the agricultural and economic sectors of the country, covering approximately 15% of the overall cultivated land [1]. Large-scale manufacturing and exports not only help meet domestic demands but also make a significant contribution to the global cloth economy. However, the process of cultivating cotton is fraught with many challenges, largely because of the widespread occurrence of various diseases, particularly Sooty Mold, which has a substantial influence on both crop yield and quality. Sooty Mold is the most common disease in cotton leaves, as it appears by the formation of black Mold on the leaf surface, and it is mainly caused by the presence of honeydew, which is a substance produced by sucking insects such as aphids or white flies [2], as shown in Figure 1. This disease is detrimental to the overall health of cotton plants; it diminishes photosynthesis and, in the end, may lead to the reduction of cotton fibre quality and market value [3]. Precise and timely detection is paramount for effectively managing and controlling these diseases. Hence, there is a need for innovative solutions that go beyond image-processing techniques and manual inspection steps.

Manual inspection has been employed for the diagnosis and management of cotton leaf diseases in Pakistan. This approach is inefficient, prone to errors, and susceptible to diverse human and environmental factors, highlighting the urgent need for advanced, automated, and dependable disease-detection methods [4]. Conventional approaches are based on visual inspection and the use of simple image processing methods, which are relatively inefficient and less precise than modern machine learning models [5].

Artificial intelligence, along with computer vision techniques, has completely changed precision agriculture, as it has brought a new paradigm that will lead to improved accuracy and efficiency of disease detection systems [6]. Several studies using both machine and deep learning models have demonstrated remarkable plant disease detection skills, which is a good foundation for our work [7]. The current study distinguished itself by focusing on the use of these advanced methodologies, specifically in the context of cotton agriculture in Pakistan, with the goal of addressing the subtle and frequently perplexing indications of plant diseases, as in Sooty Mold. This study pioneered the application of sophisticated deep-learning models to accurately distinguish between healthy and sooty-mold-infected cotton leaves. It further introduces a user-centric Android application that enables the real-time, efficient, and precise detection of Sooty Mold's disease, fostering immediate intervention and management.

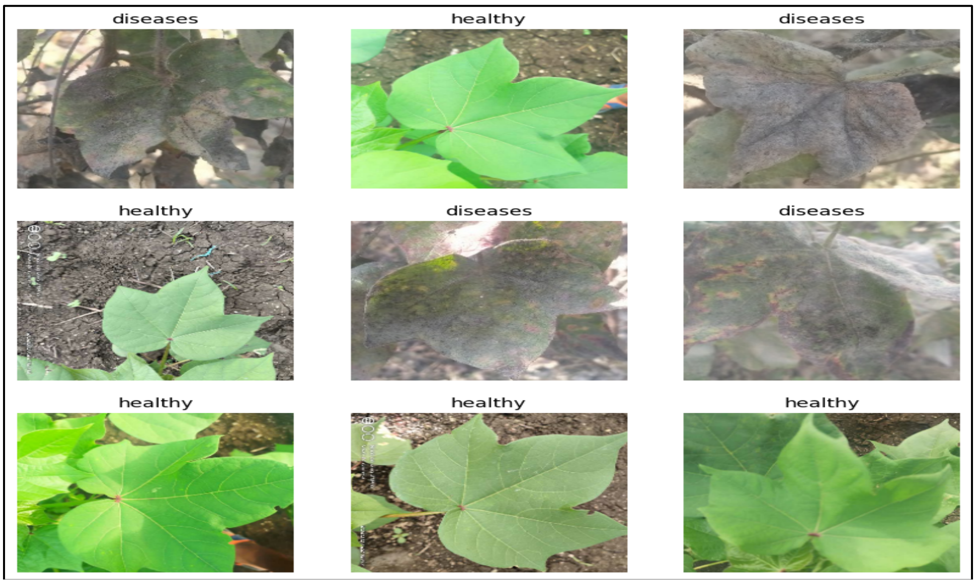

Figure 1. Comparative Display of Healthy and Sooty Mold-Infected Cotton Leaves

The remainder of this paper is organized as follows. Section II presents Related Work and discusses existing solutions and their limitations. Sections III and IV describe the Materials and Methods used, detailing the dataset, preprocessing, models employed, and application development. Section V provides a summary of the Results and Discussion of the models and their applications. Finally, Section VI concludes the study and summarizes the main findings and potential future work.

2. Related Work

Multiple landmark studies have shown that the field of agricultural disease identification at the intersection of deep learning (DL) has made tremendous progress over the past few years. Owing to DL's ability to improve the precision of plant disease feature extraction and, by extension, agricultural decision making, its use in early disease diagnosis has grown in importance in the agricultural industry. New developments in deep learning have resulted in powerful single-stage detectors such as CenterNet and You Only Look Once (YOLO). Importantly, for real-time applications in crop management, these models are significant for lowering computing requirements and accelerating detection processes. Recent research has shown that such a development is possible. For example, [8] used YOLOv5 to detect alternate thrips and Alternaria infections in citrus crops with a 99% accuracy rate. Similarly, YOLOv7 surpassed multiple DL models, including traditional CNNs, in detecting illnesses in tea leaves in natural situations with a detection accuracy of 97.3% [9].

A seminal study [10] used a meta-deep learning model in conjunction with transfer learning techniques such as VGG16 and ResNet50 to detect a wide variety of cotton leaf diseases, making further contributions to the field. They illustrated DL's ability of DL for high-level generalization in disease identification with a remarkable accuracy of 98.53% with a dataset containing 2,385 images. Moreover, [11] utilized a large dataset of 54,306 photos cut across various crop species to train a convolutional neural network (CNN), and the CNN achieved an accuracy of 99.35%. This study demonstrated the flexibility and accuracy of DL for the detection of plant diseases. In addition, [12] attained 86.6% and 89.2% accuracy using GoogleNet and ResNet50 models, respectively, for the diagnosis of cotton leaf damage. Their study focused on the application of DL to monitor the health of cotton plants so that farmers can make the right decisions concerning their crops. Similarly, [13] proposed a machine learning-based method for the visual assessment of the health of cotton leaves and the detection of diseases. Their CNN-based approach offers a possible route to a reliable diagnostic tool by forecasting the disease from the color image of a diseased leaf.

However, there are several obstacles to the effectiveness of the DL models. One such obstacle is the detection of Sooty Mold in cotton leaves, which poses unique identification challenges owing to the subtlety of disease expression and fluctuation of outdoor imaging settings. To solve this problem, [14] used architectures such as VGG16 and AlexNet to train a deep-learning ensemble algorithm using leaf photos obtained from smartphones. They achieved an accuracy of 99.04%, indicating that advanced image processing may help overcome real-world obstacles. In a broader context, a meta-analysis of research using UAV technology for remote sensing was conducted by [15], highlighting the ability of DL to identify agricultural diseases at the canopy level. One study used a UAV-mounted hyperspectral camera to accurately identify citrus cankers [16], whereas another used multispectral imaging to detect citrus greening [17], with an accuracy of 81.75 percent.

Even though these developments are revolutionary, there are still a number of obstacles to overcome, including the fact that field lighting is unpredictable and there is a weak signal difference between healthy and sick plants. In [18] and [19], the difficulties posed by the correct identification and categorization of plant diseases in outdoor settings were discussed. Our study aimed to address these issues by implementing DL methods specifically designed for the detection of Sooty Mold on cotton leaves. These algorithms are designed to work with high-resolution photos and complicated algorithms.

3. Materials and Methods

In this study, two convolutional neural network (CNN) architectures, Xception and VGG-16, were employed with caution to employ deep learning for the early detection of Sooty Mold disease in cotton leaves. These models are perfect for identifying slight but significant signs of Sooty Mold's disease because of their outstanding picture categorization skills.

3.1. Data Collection

In our dataset, we included both healthy and Sooty Mold-affected states of cotton leaves, as well as a diverse range of other high-resolution photographs. We partitioned the dataset into three parts: training, validation, and testing in proportions of 70 %, 20 %, and 10 %, respectively (Figure 2). This allowed for a more robust model training and validation. This segmentation guarantees a thorough learning environment, permits model modification to avoid overfitting, and permits the performance evaluation of fresh data to determine practicality.

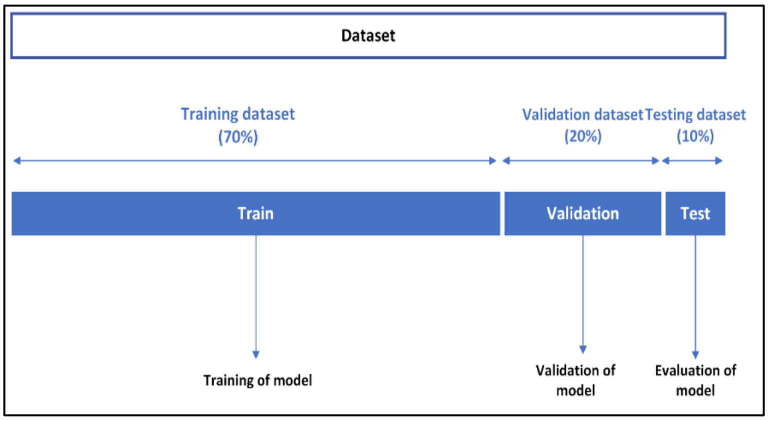

Figure 2. Dataset Division

The VGG-16 and Xception models were used to identify Sooty Mold from a training set of 695 photographs, which provided the basis for model training. A total of 251 photographs in the validation set were used to improve the generalizability of the models by refining their weights.

3.2 Preprocessing Techniques

The images must be resized and rescaled as part of the data preparation procedure for the VGG-16 and Xception models. First, all photographs were downsized to 224 × 224 pixels, which is the standard size for both models. By maximizing the trade-off between detail preservation and computational efficiency, this dimension allows for faster processing, thereby significantly reducing computational load (Figure 3).

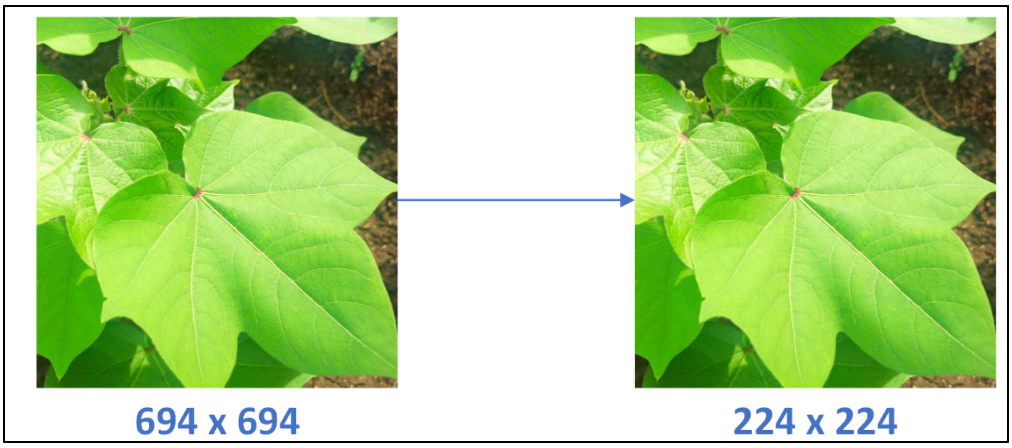

Figure 3. Resizing Process for Cotton Leaf Images

After the photos were resized, they were rescaled such that the values of each pixel were normalized to a range of 0 to 1, according to the following formula:

$$\text{rescaled image} = \frac{x}{255} \tag{1}$$

These models require normalization for numerical stability and faster convergence during training. The uniformity of the gradient scales in all the images and setting the pixel value range to a standard value improved the learning efficiency of the models. The proper training of models to recognize new, unseen inputs is accomplished by adjusting the brightness and contrast levels of the actual images. The rescaling process yields the results shown in Figure 4, representing the distribution of the pixel values as even.

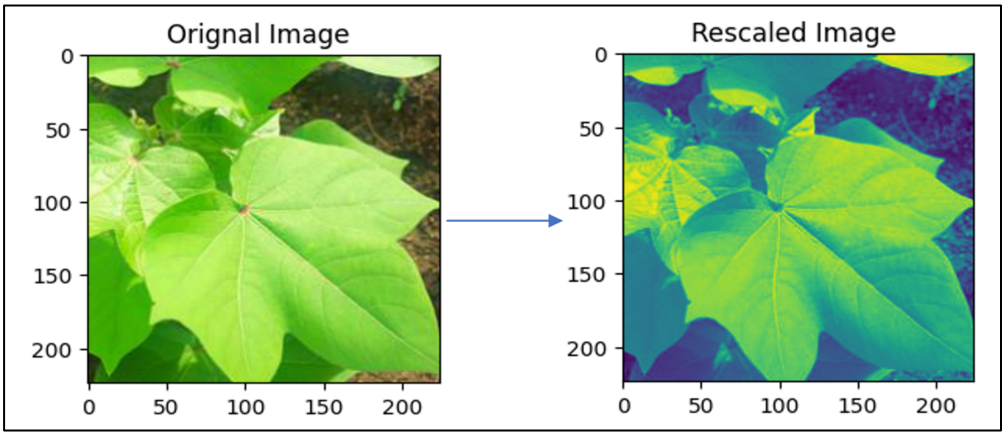

Figure 4. Normalization of Pixel Values in Preprocessed Images

3.3 Experiment-I: VGG-16 Model

3.3.1. Texture Feature Extraction

Normalization was implemented to attain numerical stability and faster model convergence. The effectiveness of our models was improved by ensuring that the pixel scales in all images were consistent with the default values. Normalization of a new type of data and making the model deal with the new inputs is an essential step in training the model to normalize the difference in brightness and contrast of natural images. The product of this remapping is presented in Figure 5, which highlights the homogeneity of the values of the individual pixels in the selected dataset.

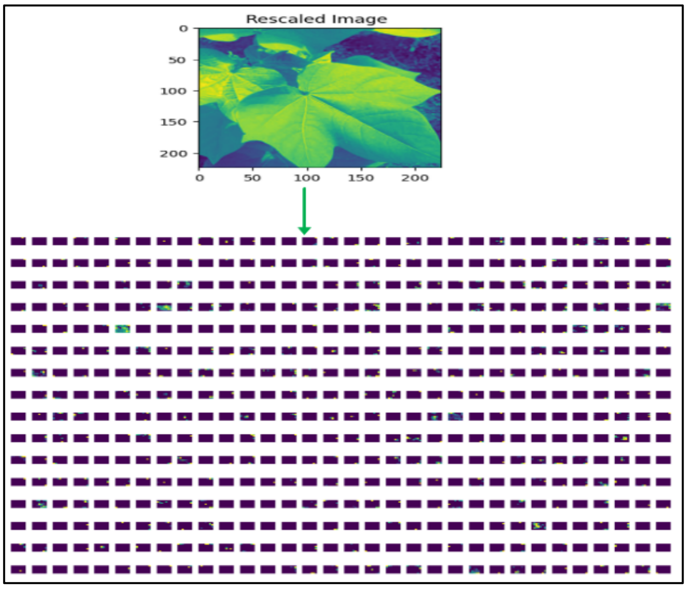

Figure 5. Pictorial Representation of Texture Features using VGG-16

3.3.2. VGG-16 Architecture and Transfer Learning

Our standardized 224 × 224-pixel cotton leaf images were easily processed using the VGG-16 architecture, which features 13 convolutional layers and three fully linked layers. The approach was improved using transfer learning, which modifies the VGG-16 model that was trained on a diverse image dataset, in our unique work of determining whether cotton leaf images are healthy or sick. The data flow through the updated VGG-16 model is illustrated in Fig. 6.

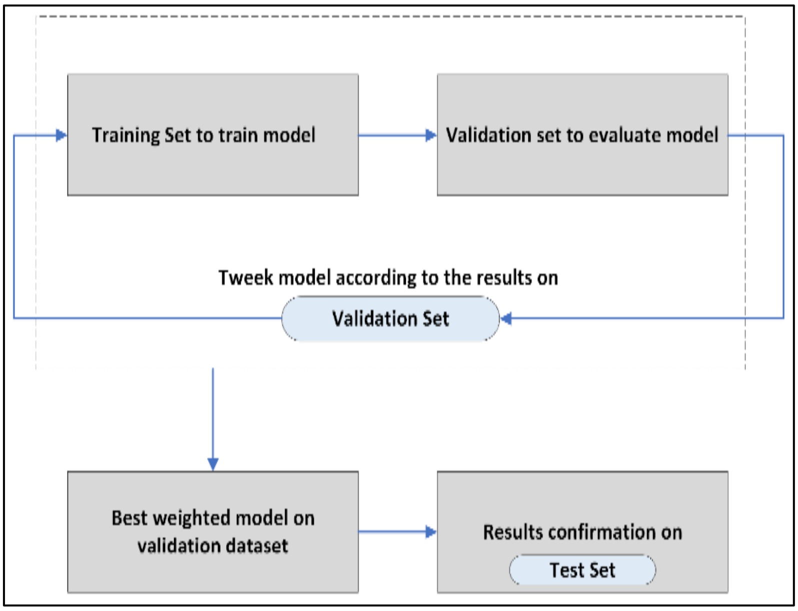

Figure 6. Transfer Learning Data Flow with VGG-16

3.4 Experiment-II: Xception Model

3.4.1 Texture Feature Extraction

The Xception model was used to extract high-level texture information from the input photos of cotton leaves, guaranteeing that the system would be able to detect sooty mold. To read out the HD picture attributes, the procedure fixes Xception's pretrained convolutional weights and zeroes on the final convolutional layer's output. Textural combinations of healthy and unhealthy leaves have been vividly introduced into life. As can be seen more clearly in Figures 7 and 8, the flexibility of this final scaled vector readout translates network understanding and data improvement into a highly generalizable descriptive representation of classification performance.

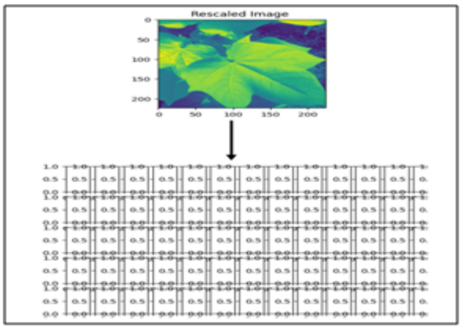

Figure 7. Texture Identification via Xception

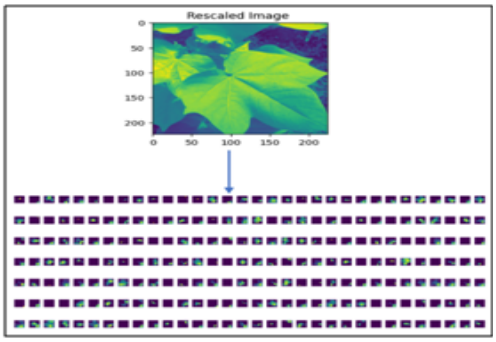

Figure 8. Pictorial representation of texture features via Xception model

3.4.2 Xception Architecture and Transfer Learning

The capacity of the Xception model to classify Sooty Mold cotton leaf disease was substantially improved by a methodology that employs transfer learning. We tailored the model's pretrained weights and architecture to meet our unique classification requirements by drawing on the information and features stored in the Xception layers, which were previously trained on a massive dataset. The model can diagnose Sooty Mold's disease by fine-tuning the learned representations. As illustrated in figure 9, the transfer learning approach not only speeds up model creation, but also guarantees strong classification performance by utilizing the design of separable convolutions. Owing to its complex multistage design, the Xception model is a powerful tool for detecting diseases in cotton leaves by efficiently performing image classification and extracting important information.

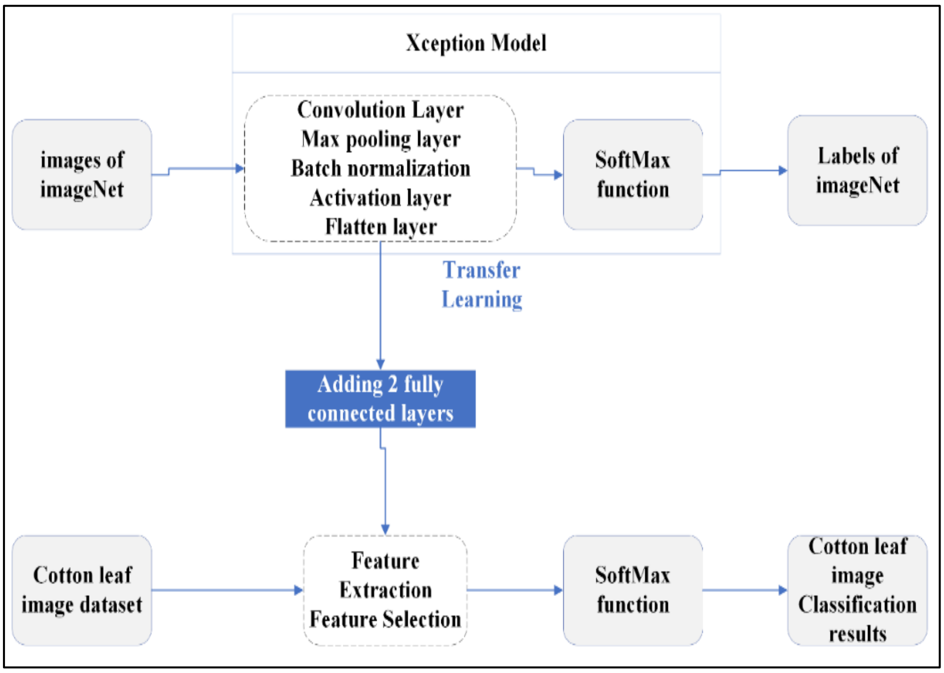

Figure 9. Workflow Diagram of Transfer Learning with Xception Model

3.5 Hyperparameter Settings for VGG-16 and Xception Models

A standard set of hyperparameters was used for the VGG-16 and Xception models for the Sooty Mold classification of cotton leaves because of their track record for optimizing model performance. When these hyperparameters are strictly followed, it becomes much easier to test how well the VGG-16 and Xception models detect the Sooty Mold on cotton leaves in a controlled setting. This standardized method streamlines training and guarantees that variations in model topologies rather than training configuration variants are responsible for any reported performance disparity. These settings are concisely represented in Table 1, which guides our approach toward high categorization accuracy.

Table 1. Hyperparameters of VGG-16

Sr. No.	Hyperparameter Name	Value/Name
1	Optimizer	ADAM
2	Batch size	32
3	Number of Epoch	50
4	Loss function	Categorical Cross entropy
5	Early stopping	True

4. Development of Android Application

Using the Android framework, a real-time application was developed for detecting Sooty Mold illnesses in cotton plants. This integration offers a two-way photo analysis mechanism: "Capture Image" and "Select from Gallery." Our goal was to build an easily available, accessible, and remote diagnostic platform. This range of interactions allows for a case-by-case solution to diagnose Sooty Mold's sickness, adapting to Pakistani farmers' urgent needs and temporary nature. As shown in Figure 10, the main objective is to offer a simple and effective way to detect Sooty Mold early, so that impacted crops can be managed and treated in a timely manner.

Figure 10. User interface for selecting image

4.1 Technologies Used

The app was developed with the help of Android Studio and the Flutter framework, with Dart being the programming language utilized. Android Studio, the central development environment, provides a full array of tools for efficiently creating and testing apps. One way to build natively built apps for the mobile, web, and desktop is Google's UI toolkit Flutter. Its ability to work across platform streamline development by doing away with platform-specific codebases. The development was built on top of the Dart language, which is well-known for its client-optimized features that allow fast apps on any platform. This guarantees that the app will run smoothly and respond quickly to all devices. Cotton leaf photos can be easily classified into healthy or ill groups using the visual patterns of Sooty Mold owing to the inclusion of the TensorFlow Lite Flutter plugin, which allows the utilization of machine learning models within the app.

4.2 Implementation Details

The app's development was dependent on the use of Dart for coding, because of the efficiency of making cross-platform apps that are both fast and scalable. Because of the TensorFlow Lite Flutter plugin, we were able to incorporate TensorFlow Lite models into the app; hence, we could analyze the images in real time and diagnose diseases. This model administration is streamlined, data pre- and post-processing are performed efficiently, and it is mobile optimized. The app has been made simple and efficient in design such that it is easy to use and navigate; therefore, it can facilitate a quick diagnosis of the disease. With a combination of these innovative technologies and tools, we have designed an app that not only detects diseases rapidly but also aims to reduce the impact of diseases such as Sooty Mold on cotton farming by deploying machine learning.

5. Results and Discussion

5.1. Results of VGG-16 Model

An exhaustive evaluation of the discriminative capabilities of the model was performed using the dataset, which included high-resolution photographs of both healthy and sick leaves. The model was thoroughly evaluated after a lengthy training period, and the results are summarized in Figure 11. An impressive training accuracy of 99.43% and a validation accuracy of 99.40% demonstrated the outstanding classification performance of the model. The model was effectively able to classify the leaves as healthy or infected with Sooty Mold because there was hardly any room for errors. During training, the model attained a precision of 99.50%; during validation, the equipped model exhibited an accuracy of 99.45%. This observation suggests that the model is accurate and that it almost never incorrectly classifies unhealthy leaves as healthy leaves. The model detected the majority of the cases accurately with little false negative instances since the values of the recall and precision rates are closely related.

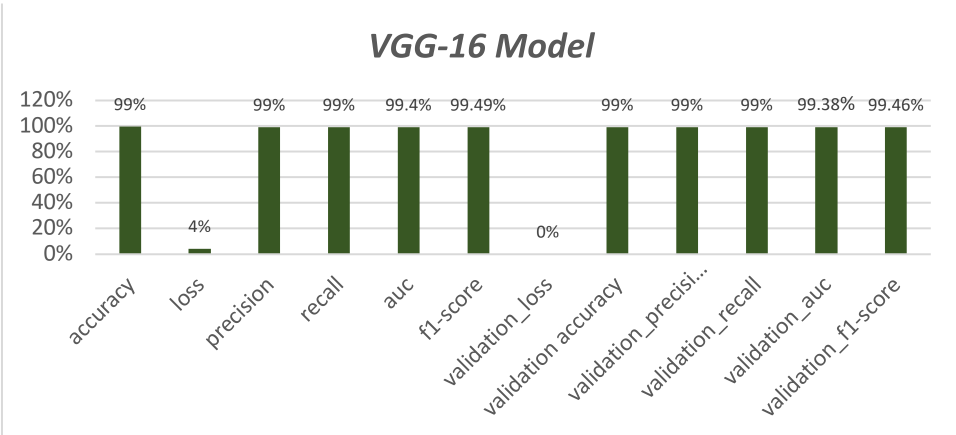

Figure 11. Comparative Evaluation Metrics of the VGG-16 Model for Sooty Mold Disease Classification in Cotton Leaves

The model with an F1-score of 99.49% during training and 99.46% during validation demonstrated balanced performance in terms of precision and recall. Given the degree of damage posed by both false positives and false negatives in an operational environment, this number is paramount in confirming the trustworthiness of the model. The Area Under the Curve of the model reached 99.40% and 99.38% during training and validation, respectively, with a remarkable AUC score of 99.38%. The AUC of the model reveals its reliability in the prediction of Sooty Mold across different cut-offs, which is particularly important when the cost of misclassification is high. With the mechanism of early stopping, the training stopped when the model's improvement became stable, so that overfitting and unnecessary computing consumption were reduced. The model training ended after 12 epochs, as indicated by this mechanism.

5.2 Results of Xception Model

The Xception model was found to be useful for detecting the occurrence of Sooty Mold's disease in cotton leaves, as illustrated in Figure 3, with a training accuracy of 99.6% and validation accuracy of 99.55%. The excellence of the model was further seen in the AUC of 99%, which indicated that the model could discriminate well. Interestingly, the loss metrics exhibited a precision of 0.04% for training and 0.0645% for validation. These values demonstrate the model's ability to generalize effectively from data to unseen data, while maintaining a balance between sensitivity and specificity.

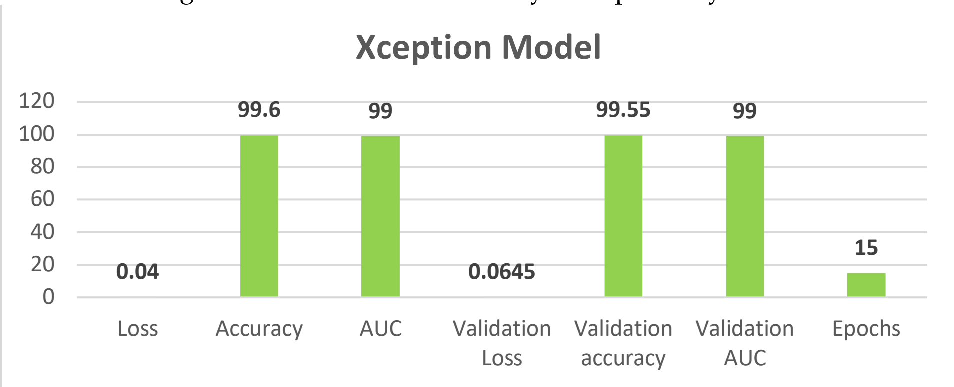

Figure 12. Performance Metrics of the Xception Model

After 15 epochs, the model remained efficient, without being susceptible to overfitting. This strategy optimizes the training process by identifying the ground between learning and computational resource usage. These findings highlight that the Xception model is promising as a tool for real-time disease detection, potentially transforming disease management practices in cotton farming. This tool can not only provide a diagnosis but also help prevent disease spread, thereby safeguarding crop yield and quality. The results of the model predictions are shown in Figure 13. A set of 16 images was randomly selected as the input for the model predictions and was correctly classified with their labels.

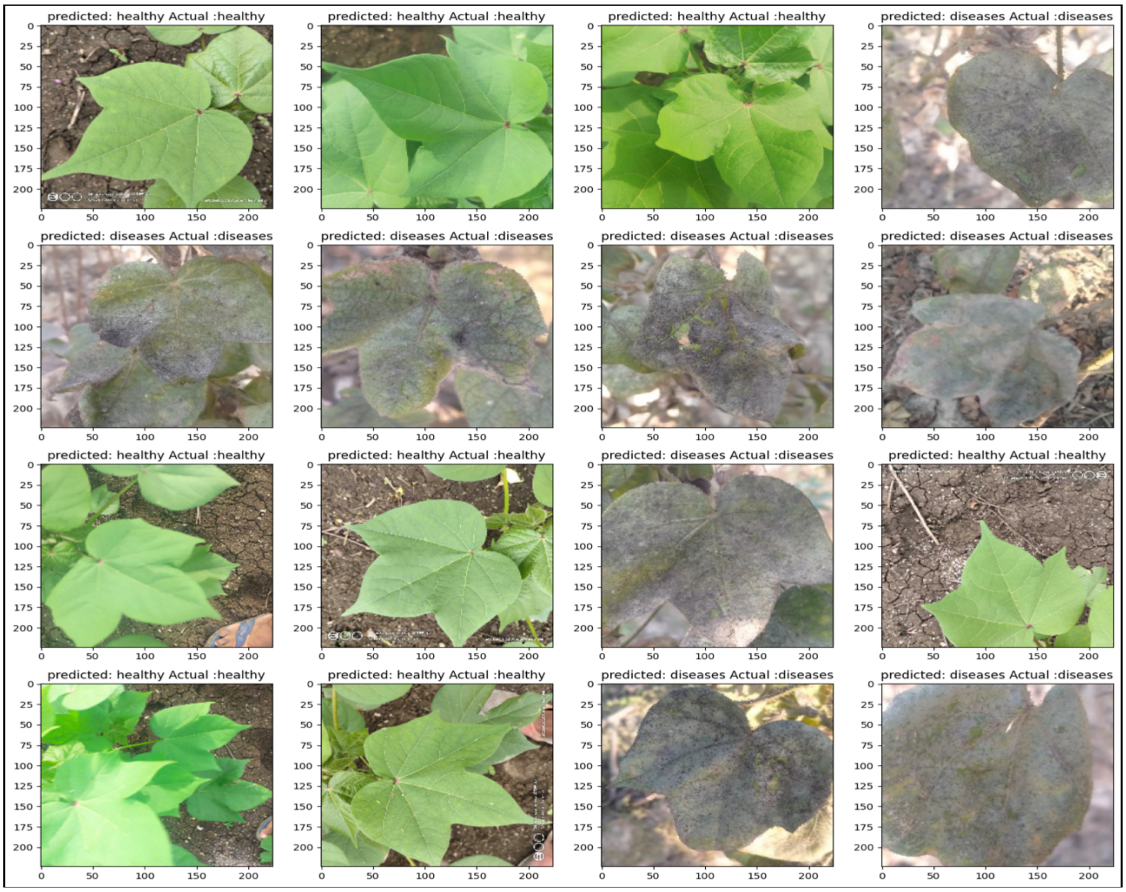

Figure 13. Prediction results of Xception model

5.3 Evaluation of the Android Application

In field tests, the Android app that was created to identify Sooty Mold in cotton leaves in real time performed exceptionally well. The program employs a trained model to examine user-uploaded cotton leaf photos, and then provides a diagnosis along with relevant accuracy rates. As shown in Figure 15, the application successfully detected sooty mold disease from an uploaded image with a 99.98% precision. In contrast, the application confirmed a healthy leaf with a flawless accuracy score of 100%, as shown in Figure 14. These outcomes demonstrate the diagnostic relevance of the app by demonstrating its ability to differentiate between healthy and diseased leaves. With its impressive accuracy in test circumstances, the application shows great promise as a valuable tool for researchers and farmers in the fight against sooty mold. Prompt action is essential to keep crops healthy and maximize agricultural output. All users, regardless of their level of technical expertise, will be able to take advantage of the app's extensive features owing to its clean and simple user interface.

5.4 Comparative Analysis and Discussions

Numerous studies have been conducted on agricultural disease detection, and while models such as VGG-16 are not considered cutting-edge in the rapidly expanding machine learning environment, their resilience in picture categorization is noteworthy. VGG-16 has been proven to be effective, even though it is simple in different applications, such as object detection and disease classification. With the design of its architecture consisting of 16 layers of tiny 3 × 3 filters, it was created to capture minute details in photographs, which is essential in differentiating subtle elements, including sooty mildew on cotton leaves. Nevertheless, with the help of invention ideas such as skip connections and inception modules, the model's complexity would be reduced, and the training time would be significantly less. On the other hand, the Xception model, which is characterized by a complex multiple-phase architecture, performs well when the disease under consideration is the sooty mold cotton leaf. The combination of convolutional, batch normalization, and activation layers achieved the purpose of detecting the basic patterns of cotton leaf images in the early stages. The application of depth-wise separable convolutions in Xception is not only effective in feature extraction but also has lower memory requirements.

Figure 14. App Interface for Healthy Leaf Verification and Disease Detection

In our investigation, both models were modified to address the inadequacies observed in earlier publications [20], [21]. We were able to achieve more accuracy at a lower processing cost using techniques like data splits and early stopping. The models' performance was evaluated using precision, recall, F1-score, and AUC, which returned a high accuracy score and generalization that was able to detect the sooty mold cotton leaf disease. On the other hand, the application we made relies on the aforementioned models for easy and user-friendly environment for real-time disease identification. Fig 15 brings VGG-16 and Xception comparatively together, which shows that Xception excels at feature extractions and categorization. The peculiar structure of Xception enables it to process images at high speed and with a high accuracy when detecting disease symptoms. The advantage of this low computational approach lies in its ability to precisely diagnose agricultural diseases.

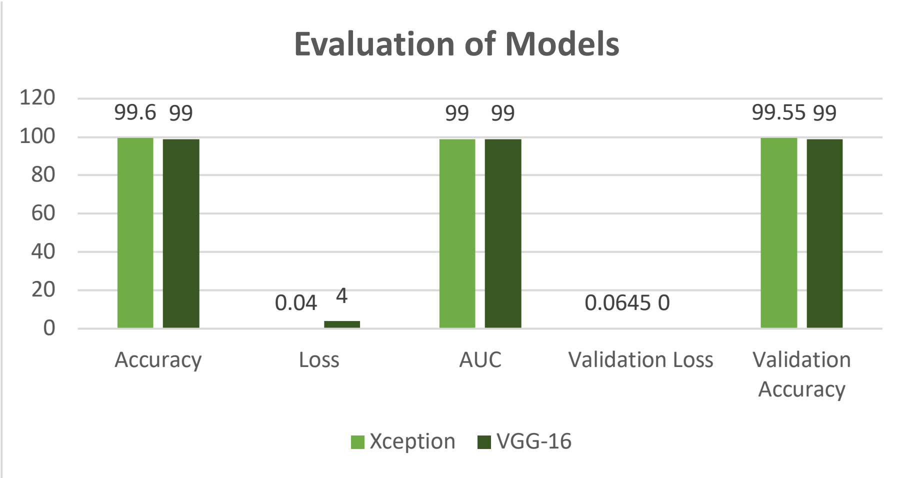

Figure 15. Performance Comparison of VGG-16 and Xception Models

6. Conclusions and Future Work

This trial experiment showed that modern convolutional neuronal network designs, such as VGG-16 and Xception, are able to correctly diagnose sooty mold disease on cotton leaves. This study highlights the significance of deep learning techniques in revolutionizing the agricultural sector by providing dependable, efficient, and rapid disease-detection tools. The models produced attained a superb accuracy in diagnosing Sooty Mold, and the Xception model slightly overperformed VGG-16, thus demonstrating its superiority over complicated image recognition problems resulting from the deep convolutional separable layers. Additionally, the integration of these models into an Android application with a user-friendly interface is extremely helpful for farmers, researchers, and decision-makers who need real-time detection of disease status to take appropriate actions in a timely manner and avoid crop loss. The main outcomes of this study are valuable in recognizing the phenomenon of precision, particularly disease identification and control. Nevertheless, there are still many opportunities for further research and development.

In future studies, more varied datasets that would include a wider spectrum of cotton leaf diseases should be used to fine-tune the system and make it more complete. The analysis of different existing deep learning architecture models and optimization methods makes the existing model more efficient. Moreover, enabling the app to provide therapeutic options for disease management and alternative treatments would complement its capability to guide farmers on objective technical issues. Finally, application testing and feedback from end users are imperative to ensure that it meets the needs of farmers. This can only be achieved through deployment in various environmental scenarios.

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