An Advanced Deep Learning Approach for Precision Diagnosis of Cotton Leaf Diseases: A Multifaceted Agricultural Technology Solution

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ABSTRACT

During the past few decades, cotton leaf diseases have become a significant challenge for farmers, leading to substantial losses in harvests, productivity, and financial resources. Traditional observation methods are often time-consuming, costly, and prone to inaccuracies, exacerbating the plight of farmers in detecting and identifying diseases in their early stages. The consequences of late detection are dire, and both crops and farmers are under the brunt of prolonged infections. This study proposes a method to improve the detection of cotton leaf diseases by applying advanced deep transfer learning techniques. Using models such as ResNet101, Inception v2, and DenseNet121, and fine-tuning parameters utilizing the Nesterov accelerated gradient, the proposed system offers a powerful tool for farmers to swiftly and accurately diagnose leaf diseases. This system allows users to simply upload an image of a cotton leaf. After sophisticated image processing techniques, a Convolutional Neural Network (CNN) is deployed to detect the presence of cotton leaf diseases with high precision and efficiency. The experimental results demonstrated the effectiveness of transfer learning approaches, with the CNN achieving an impressive accuracy of 99%, while ResNet101, Inception v2, and DenseNet121 achieved 75.36%, 97.32%, and 97.16%, respectively. These findings underscore the potential of deep learning techniques to revolutionize disease detection in agricultural contexts, offering farmers a powerful tool to mitigate the impact of diseases on their crops.

Keywords-CNN; Deep Learning; Resnet101; Inception v2; Densenet121; Nesterov accelerated

I. INTRODUCTION

Most of the Indian territory is dedicated to agriculture, providing stability for the country's economy [1]. Several different diseases impede the development of crops in fields, leading to a significant drop in the quality of the final product. Cotton diseases that severely affect production, such as insect infestation, charcoal rot, and others, cause a progressive decline in India's cotton production every year, decreasing the productivity and income of farmers. Farmers can use pesticides to protect their crops from diseases in the early stages of growth. Insects, fungi, and other microscopic pests are primarily responsible for the quality and quantity of crop failures associated with diseases, causing devastating losses for many farmers [2, 3]. Farmers face a difficult task in early disease detection in crops, as this requires their presence. The early and accurate diagnosis of crop diseases is crucial [4]. Farmers usually rely on their experience to examine cotton leaves with the naked eye and observe conditions. Usually, plant pathologists investigate cotton diseases following the traditional approach, which takes a long time and can lead to false diagnoses. In addition, pesticide use may be excessive or inadequate. Therefore, an automatic method to detect cotton diseases is substantial to keeping an eye on large crop fields and early identification. This type of system can be implemented using machine learning, image processing, and neural network techniques. With advances in image processing techniques, these problems can now be addressed quickly, consistently, and elegantly. This study builds on previous work that employed convolutional neural networks (CNNs) to detect diseases in cotton leaves, providing better methods to detect infections generated by bacteria and environmental factors.

Cotton is the highest-ranked commercial crop in India. This essential crop provides thousands of farmers in developed and developing countries with high-paying incomes. The textile industry worldwide is dependent on cotton. As cotton diseases are mostly transmitted by the leaves of the cotton plant, this study investigates the cotton leaves instead of the plant. Fungal diseases and cotton foliar leaf spots are among the ailments that affect cotton foliage. In recent years, researchers have become more interested in sustainable agriculture, which encompasses a variety of agricultural complications, such as the plantation cycle, efficient resource use, and crop lifetime. Crop life cycle encompasses not only its growth, but also its prevention and diagnosis of diseases. The importance and influence of leaf diseases on plant growth are demonstrated by the increase in research and surveys on the subject. Cotton leaf diseases have financial implications measured throughout the cotton production chain. Additionally, farmers not only lose revenue due to low production, but also need to invest to manage diseases, such as buying fungicides or pesticides. These costs negatively influence the economies of individual farms and also entire agricultural industries within the cotton production chain. Furthermore, the consequences of cotton leaf diseases do not remain within a single farm but cover the entire economies of the most affected agricultural sectors. In regions where cotton farming is one of the most important aspects of rural life, such as Central Asia or sub-Saharan Africa, such diseases can disrupt the economic stability of the country, reducing income and living standards and increasing malnutrition levels. Therefore, delving deeper into the intricate interplay between these diseases and economic variables sheds light on the challenges faced by cotton farmers and adittionally underscores the urgency of concerted efforts to mitigate their impact and ensure the resilience of global cotton production systems.

II. LITERATURE REVIEW

In [5], automatic snapshots of crops at every stage were used to detect diseases by employing a multi-SVM technique to segment and classify different diseases. In [6, 7, 8], ANNs were utilized to classify leaves as healthy or diseased. As Multi-SVMs are less likely to overfit, they are more effective than CNNs. In [9], a deep CNN was employed to detect cotton leaf diseases. In [10], the Random Forest algorithm was applied to detect cotton leaf diseases. In [11], a 2D-CNN was used to classify cotton leaves as healthy or diseased. In [12], several image pre-processing techniques and machine learning models were implemented to detect cotton leaf diseases, achieving an accuracy of 94.56%. In [13], deep learning frameworks, such as CNN, were utilized to classify cotton leaves as healthy or diseased. The load position in the crop leaf was determined using multimodal criteria with the help of the SVM technique. In [14], deep learning and transfer learning approaches were adopted to detect cotton plant leaf diseases. In [15], a deep adversarial network, called CropCycleNet, was put into service to study the behavior of healthy and unhealthy cotton plants to better analyze factors such as plant growth and maturity. In [16], CNN and transfer learning techniques, such as Alexnet and Mobilenet, were deployed to detect plant leaf diseases. In [17], a novel deep-learning pipeline was proposed to detect cotton plant leaf diseases.

In [18], SVM was more accurate than other algorithms in detecting cotton leaf diseases. In [19, 20], various transfer learning techniques, such as Densenet121 and Cropnet architectures, were employed to classify cotton leaf diseases. In [21], ensemble models were implemented to classify cotton leaf diseases with the help of optimizers, such as gradient descent. In [22], the severity of fusarium oxysporum disease in cotton was assessed using unmanned aerial images and a hybrid domain adaptation deep learning time series model. This method improved the spatio-temporal transferability of the CNN-BiLSTM model, allowing it to leverage historical datasets more efficiently. The CNN-BiLSTM model performed better than conventional time-independent machine-learning techniques that relied on manually designed features. In [23, 24] conventional approaches, such as CNNs, were utilized to classify cotton leaves. In [25, 26, 27], image processing and machine learning techniques were followed to identify plant and animal diseases. In [28], six pre-trained deep learning models, namely DenseNet121, DenseNet169, MobileNetV2, ResNet50V2, VGG16, and VGG19, were used, along with image augmentation techniques, to identify bacterial blight and curl virus in cotton leaves. The results showed that DenseNet169 and ResNet50V2 achieved the highest accuracy. In [29], a CNN outperformed other models in detecting cotton leaf curl disease.

III. METHODOLOGY

The study employed CNN algorithms for precise image classification and disease detection. Figure 1 portrays the architecture of the system, illustrating the sequential stages involved in the analysis process. Upon initiation, the system requires the user to provide an image of a cotton leaf for analysis, which serves as input for subsequent processing steps. Before applying the CNN method, the uploaded image undergoes pre-processing to enhance its suitability for feature extraction and classification. The core of this method lies in the use of CNNs for feature extraction and disease recognition. Through a series of convolutional layers, the CNN algorithm automatically identifies key features within the input image, facilitating accurate disease detection. This feature extraction process is crucial for distinguishing between healthy and diseased cotton leaves, enabling the system to categorize the leaves into relevant classes. To certify the robustness of the classification process, the system compares the extracted features from the input image to a pre-trained dataset. This dataset contains a diverse array of cotton leaf images that cover various disease states and environmental conditions. Using this extensive training dataset, the system improves its ability to accurately classify and identify diseases in cotton leaves. Furthermore, the CNN architecture allows for adaptive learning, enabling the system to continually refine its classification capabilities based on new input data. This adaptive learning mechanism ascertains that the system remains effective in detecting emerging diseases and adapting to changing environmental factors.

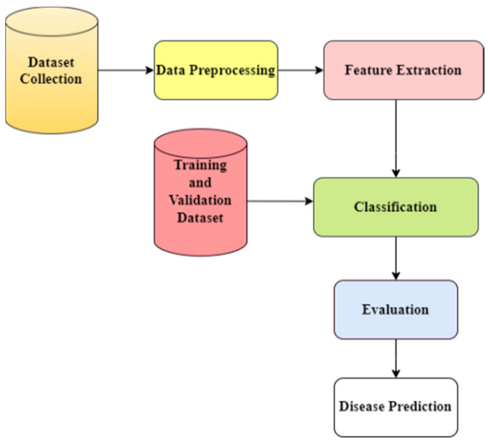

Fig. 1. Proposed method.

A. Dataset

The dataset used [30] was meticulously curated to encompass a comprehensive representation of cotton leaf conditions, comprising images from four distinct classes. These classes include healthy cotton leaves, diseased cotton leaves, as well as healthy and diseased cotton plants. The healthy cotton leaves exhibit no signs of disease or infestation. Leaves with bacterial blight, affected by bacterial infections, typically show water-soaked spots that turn dark brown. Fungal disease leaves demonstrate symptoms of fungal infections, such as yellow or brown spots. Virus diseases display signs of viral infections, which may include mosaic patterns or discoloration. In total, the dataset comprises 2616 high-resolution images that capture the diversity of cotton leaf conditions encountered in real-world agricultural settings. 1951 leaf images were used for training, and the remaining 665 images were utilized for testing. Each image provides valuable insights into the visual characteristics associated with different stages in cotton plants. By incorporating a variety of conditions, from pristine foliage to symptomatic manifestations of disease, the dataset facilitates robust learning and enables the system to accurately distinguish between various states of plant health. The comprehensive nature of the dataset ensures that the classification system is equipped to handle the complexities and nuances inherent in real-world agricultural scenarios. This rich dataset serves as a foundational resource for developing and validating the classification model, ultimately enhancing its applicability and reliability in practical settings.

Fig. 2. Augmented cotton leaf images: (a) fresh cotton plant, (b) fresh cotton leaf, (c) diseased cotton plant, and (d) diseased cotton leaf.

B. Data Augmentation

Data augmentation is a crucial strategy to enrich the training dataset and enhance the ability of models to generalize their learned features to new images. Image data augmentation involves creating alternative versions of images employing a range of transformations while preserving their underlying classification. These transformations introduce variations that simulate real-world scenarios and augment the dataset with additional instances, enabling models to learn from a more comprehensive range of visual representations. The need for data augmentation arises from the substantial data requirements of deep learning models. This study applied rotation, flipping, zoom, cropping, brightness and contrast adjustment, and noise-adding data augmentation to enhance the robustness and generalization ability of the models. The images were rotated to a certain degree (40°) to simulate different orientations of the leaves, both horizontal and vertical. Images were flipped horizontally and vertically to increase variability. The images were also randomly scaled to create scale variations. Randomly cropping parts of the images were used to simulate partial views. The brightness and contrast levels were varied to mimic different lighting conditions. Random noise was added to make the model more robust to variations. These augmentation techniques were applied uniformly across all images in the dataset to ensure consistency in training.

C. Architecture

CNNs evolve from the foundation of multilayer perceptron, yet they are distinctively engineered to harness a suite of powerful convolutional filters. These specialized networks are adept at dissecting various structural elements within images, offering a nuanced analysis that was previously unattainable with traditional methods. The architecture of a typical CNN involves a fully connected layer that caps a series of convolutional and pooling layers. At the heart of the convolutional layers lies a battery of kernels that identify and analyze specific features within visual data. Following every convolutional phase, a pooling layer typically intervenes, with its primary function being to condense the size of the feature map by either averaging or selecting the maximum values within predefined sections to distill broad patterns from the imagery. Even when scaled, these images continue to manifest these overarching patterns, illustrating the crucial role of the pooling layer in maintaining the integrity of visual information. This streamlined process facilitates the identification of large-scale patterns within the images, ensuring that even scaled versions retain their distinctive characteristics. Figure 3 displays the CNN architecture. CNNs are constructed in a way that allows them to consider the spatial structure of the input. Hidden layers in a CNN typically include convolutional, pooling, fully connected, normalization, and ReLU (activation function) layers to automatically extract features.

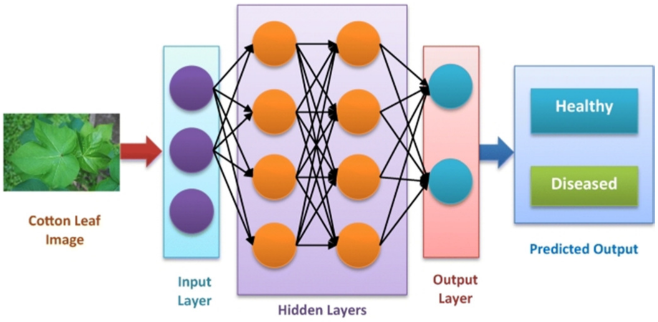

Fig. 3. CNN architecture for cotton leaf disease detection.

IV. RESULTS AND DISCUSSION

The proposed model for identifying cotton leaf diseases was developed using Python 3.8, on a PC with 8GB RAM and an NVIDIA GPU. This CNN utilized a 224×224 matrix as input. Convolutional filters of size 3×3 were deployed in the first layer. ReLU was used as the activation function, and the output matrix was zero-padded to preserve the input's geometry. A second convolution layer followed, having 32 3×3 filters with a ReLU activation function to process the layer's output. A max pooling layer with a 2×2 kernel and a stride of 2 received the output. Its output was sent to a dropout layer, where 25% of the neurons were randomly removed to prevent the model from overfitting the data. Then, a convolution layer with 64 filters, kernel size of 3×3, and the ReLU activation function was applied to the output of the dropout layer. An additional convolution layer followed, using 64 filters and a 3×3 kernel size. Categorical cross-entropy was deployed as the loss function during the compilation of the specified Keras model. The weights were adjusted in response to the loss gradient. A learning rate of 0.0001 was utilized along with the Adam optimizer. The model was trained with a batch size of 32 for 500 iterations.

Pre-trained models, including ResNet101, Inception v2, and DenseNet121, were employed to leverage transfer learning. These models were implemented using the TensorFlow library for ResNet101 and DenseNet121, and the Keras library for Inception v2. The same data augmentation techniques were applied across all pre-trained models to maintain consistency. Learning rate was tuned using a learning rate scheduler, and the Nesterov Accelerated Gradient (NAG) optimizer was utilized for all models. Different batch sizes (32, 64, 128) were used to find the optimal size, and the number of training epochs was set to 50, incorporating early stopping based on validation loss to prevent overfitting. Figures 4 and 5 demonstrate the accuracy and loss of the CNN model. The training and testing ratio was consistently fixed at 80:20 for all experiments. Figure 6 manifests the loss of the Resnet-101 model and Figure 7 exhibits its accuracy (75.36%).

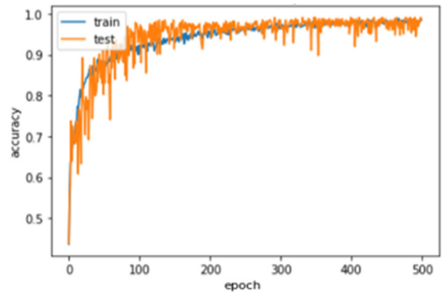

Fig. 4. CNN model accuracy.

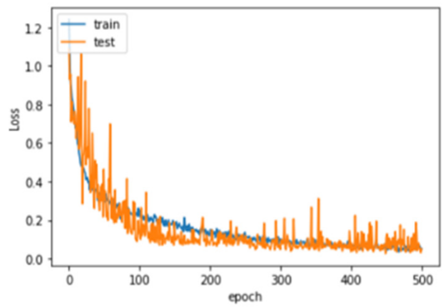

Fig. 5. CNN model loss.

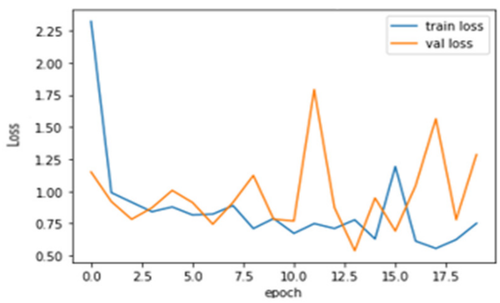

Fig. 6. Resnet-101 model loss.

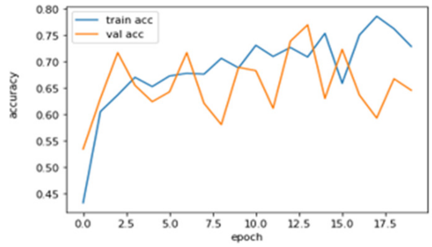

Fig. 7. Resnet-101 model accuracy.

The accuracy of the Inception v2 model was 97.38% and Figure 8 shows its learning graph. The accuracy of the Densenet-121 model was 97.16%, as evidenced in Figure 9, while Figure 10 presents its loss.

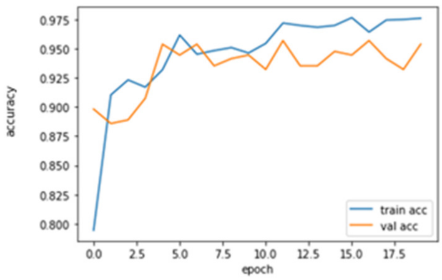

Fig. 8. Inception v2 model accuracy.

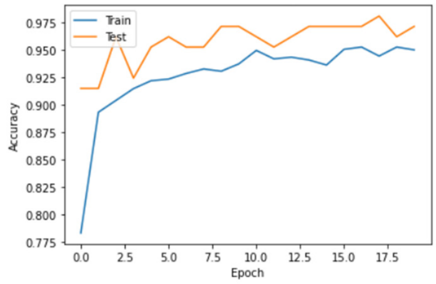

Fig. 9. Densenet-121 accuracy.

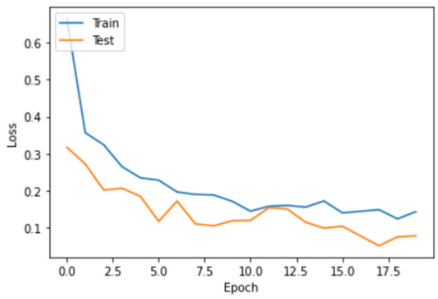

Fig. 10. Densenet-121 loss.

The NAG optimization technique was followed to adjust the model parameters and improve the weights and bias. The formula to calculate the Nesterov accelerated gradient is given by:

$$W_{look_{ahead}} = Weight - \gamma\,.udate_{t-1} \qquad (1)$$

where: γ is the decaying hyper-parameter that establishes the rate of decay of accumulated prior gradients, η represents the momentum, and ∇ represents the velocity:

$$udate_{t-1} = \gamma\,.update\ t - 1 + \eta\nabla \times W_{look\_ahead}$$

$$W_{t+1} = W_t\,.update_t$$

Figure 11 portrays the confusion matrix juxtaposing the actual occurrences of a given class with the predicted instances ascribed to it. The confusion matrix not only underscores the adaptability and efficiency of the transfer learning models, but also illuminates the path toward refining their accuracy through the strategic adjustment of parameters.

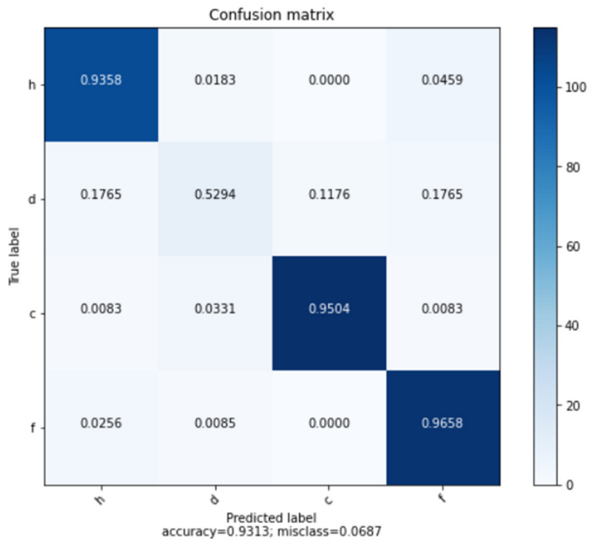

Fig. 11. Confusion matrix for CNN.

The calculations for the confusion matrix are as follows. Accuracy is the classifier's ratio of accurate predictions to total predictions produced by all classifiers, given by:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \qquad (2)$$

Precision denotes the true positive observations to the total predicted positives. For class i, it is calculated as:

$$Precision_i = \frac{True\ Positives_i}{True\ Positives_i + False\ Positives_i} \qquad (3)$$

Recall is the ratio of correctly classified positive observations to all observations in the actual class. For class i, it is calculated as:

$$Recall_i = \frac{True\ Positives_i}{True\ Positives_i + False\ Negatives_i} \qquad (4)$$

F1-Score is the harmonic mean of precision and recall for class i, as given by:

$$F1 - Score_i = 2 \times \frac{Precision_i \times Recall_i}{Precision_i + Recall_i} \qquad (5)$$

The micro-averaging method was used for multiclass evaluation. This method aggregates the contributions of all classes to compute the average metric and is useful for evaluating the overall performance of the model. This approach treats all classes equally.

$$MacroPrecision = \frac{1}{N}\sum_i Precision_i \quad (6)$$

$$MacroRecall = \frac{1}{N}\sum_i Recall_i \quad (7)$$

$$MacroF1-Score = \frac{1}{N}\sum_i Score_i \quad (8)$$

Weighted averaging calculates the metrics for each class by taking the average weighted by the number of true instances for each class. Weighted precision is given by:

$$\sum_i \left(\frac{\text{True Positives}_i + \text{False Negatives}_i}{\text{Total Instances}} \times \text{Precision}_i\right) \quad (10)$$

Weighted recall is given by:

$$\sum_i \left(\frac{\text{True Positives}_i + \text{False Negatives}_i}{\text{Total Instances}} \times Recall_i\right) \quad (11)$$

Weighted F1-Score is given by:

$$\sum_i \left(\frac{\text{True Positives}_i + \text{False Negatives}_i}{\text{Total Instances}} \times F1-Score_i\right) \quad (12)$$

A user interface was developed using the Flask framework to demonstrate the results observed in Figures 12 and 13. The user needs to upload a cotton leaf image to get informed if it is healthy or diseased.

Fig. 12. Healthy cotton plant.

Fig. 13. Diseased cotton plant - attack of leaf-sucking and chewing pets.

Table I compares the proposed CNN with Resnet101, Inception v2, Densene121, and the CNN in [14]. The proposed CNN obtained superior accuracy, as the other architectures possibly suffered from overfitting. The proposed CNN achieved approximately 99% accuracy, precision, recall, and F1 score. Resnet101 had 75.16% accuracy, Inception V2 had 97.38% accuracy, and Densenet121 had 97.16% accuracy. Due to the fever number of dropouts in the other transfer learning models, the accuracy was reduced compared to the proposed CNN.

TABLE I. MODEL COMPARISON

Architecture	Accuracy	Precision	Recall	F1-Score
Resnet101	75.36	76.30	77.80	78.30
Inception v2	97.38	97.60	97.20	97.80
Densenet121	97.16	98.60	98.20	98.70
This study's CNN	99.00	98.90	99.00	99.00
CNN [14]	92.23	93.21	90.45	94.90
CNN [20]	91.00			

V. CONCLUSION AND FUTURE SCOPE

This study demonstrates the efficacy of employing CNNs to detect cotton plant diseases using digital color images of leaves. The overarching goal of the proposed system is to provide farmers with a robust tool for swiftly and accurately identifying crop diseases, enabling timely intervention and mitigation measures to protect agricultural yields and livelihoods. The proposed CNN achieved an impressive detection accuracy of 99%, highlighting the potential of deep learning techniques to revolutionize disease detection in agricultural contexts. Moving forward, there are numerous avenues for future research and improvement. The integration of additional features and functionalities could improve the utility and usability of the Flask application. For instance, incorporating features, such as disease diagnosis, preventive measures, remedial actions, required pesticides, and estimated treatment costs could provide invaluable support to farmers in managing crop health. Furthermore, fine-tuning the hyperparameters of the CNN model presents a promising avenue for improving detection accuracy and robustness. Optimizing model parameters, such as learning rate, batch size, and network architecture, can potentially enhance the model's ability to generalize and accurately classify a wider range of cotton leaf abnormalities. Additionally, expanding the dataset to include a more extensive variety of cotton leaf diseases and environmental conditions would improve the system's capacity to detect and classify a broader spectrum of plant health issues. An expanded dataset could encompass diverse geographical regions, climates, and crop varieties, ensuring the adaptability and effectiveness of the model in different agricultural contexts. Furthermore, the development of a user-friendly interface and a mobile application could facilitate the widespread adoption and accessibility of the system among farmers and agricultural practitioners. Streamlining the user experience and providing intuitive tools for image upload, analysis, and result interpretation can help users leverage the system's capabilities effectively in real-world agricultural settings. In essence, this study lays the foundation for future advancements in the field of agricultural disease detection and management. Continuous innovation and refinement can contribute to the development of sustainable and resilient agricultural practices, ultimately fostering food security and economic prosperity in agricultural communities around the world.

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