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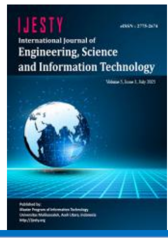

Cotton Disease Prediction Using Deep Transfer Learning: Comparative Analysis of Resnet50, VGG16 and Inceptionv3 Models

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Abstract

Cotton is among the most critical crops in the world textile industry, but it is highly susceptible to a vast array of infections that have a tremendous impact on output and fiber quality. Traditional cotton disease diagnosis is mostly based on manual inspection by farmers and experts and is time consuming, labor intensive and inaccurate due to similarity of symptoms. The high rate at which artificial intelligence, especially computer vision and deep learning (DL), have advanced has provided effective alternatives to auto-detecting plant diseases. As a subdivision of the DL approach, transfer learning allows adapting existing convolutional neural networks to the agricultural domain using smaller datasets to guarantee higher performance. This work introduces comparative analysis of three popular deep transfer learning (DTL) models ResNet50, VGG16, and InceptionV3 that are used in the classification of cotton leaf diseases. The training, validation, and testing were performed on a dataset of 1,991 labelled images that included four categories of normal and diseased cotton leaves and plants. All models were optimized and assessed with standard measures, such as validation and test accuracy. The experimental results show that InceptionV3 had the highest accuracy of 95.28, VGG16 had 85.85, and ResNet50 had the lowest accuracy of 69.81. The high accuracy of InceptionV3 is also a testament to its ability in the extraction of multi-scale features, and the trade-off between accuracy and computational efficiency. The results affirm the feasibility of DTL frameworks to revolutionize precision agriculture by facilitating diagnosis of cotton diseases in a timely and reliable manner. This development can help in ensuring that farming activities are sustainable, pesticides are used efficiently and the economy does not suffer economic losses and helps in ensuring that productivity and environmental protection are maintained in cotton farming.

Keywords: *Cotton Disease Detection, Deep Learning, Deep Transfer Learning, Resnet50, VGG16, Inception_V3.*

1. Introduction

Cotton is among the most valuable crop products grown on a worldwide basis, especially in countries like India, China, the United States, and Pakistan. Cotton is a major raw material for the textile industry, and its crucial role in keeping the global economy and livelihood of millions of cotton farmers intact. However, cotton is extremely susceptible to a wide range of diseases caused by pathogens like fungi, bacteria, and viruses, including the cotton leaf curl virus (CLCuV), bacterial blight, and alternaria leaf spot [1]. The diseases not only lower crop yields but also lower fiber quality, resulting in enormous economic loss each year.

Conventional disease detection methods rely heavily on manual visual examination by farmers or agricultural experts [2]. The method is labor-intensive, boring, and prone to human error, particularly in distinguishing among diseases with overlapping symptoms. The last couple of years have witnessed the use of artificial intelligence (AI) and computer vision in agriculture as a game-changer. Deep learning methods, specifically CNNs, have been found to be extremely useful for plant disease detection using image analysis [3]. DTL, a specialized branch of deep learning, has been shown to be a strong solution to address the limitations of small agricultural datasets. Using pre-trained models like RESNET50, VGG16, and INCEPTION_V3, which were pre-trained using large image datasets like ImageNet, researchers are able to fine-tune these models for particular agricultural uses, resulting in improved accuracy and performance [4]. Different deep learning architectures have been used for cotton and plant disease detection in different studies with promising results. However, there is a clear lack of in-depth comparative studies that compare the best-performing and most popular transfer learning models. The aim of this research is to bridge the gap by making a comparison of the RESNET50, VGG16, and INCEPTION_V3 models in the context of cotton disease prediction. It is hoped that the findings of the study will help in the selection of the most effective deep learning frameworks for real-world use in precision agriculture, especially in regions cotton cultivation is an important economic activity.

2. Literature Review

Conventional disease detection techniques are based on manual scouting, which is time-taking and subject to human error. since the development of DL and computer vision, scientists have investigated automated techniques for early and precise disease detection, significantly improving precision agriculture.

The pioneering research by Mohanty et al. used CNNs for plant disease classification using the Plant Village dataset [5]. Their work showcased the capabilities of deep learning for agriculture, while their scope was wide and did not include cotton. Ferentinos performed comparative research on deep CNN structures such as AlexNet, VGG, and GoogleNet for detecting plant diseases [6]. He noted that deep models can have excellent accuracy when sufficiently trained, stressing their use in high-accuracy classification. However, real-world performance often varies due to inconsistent lighting, background noise, and disease similarity—issues particularly common in cotton fields.

Zhang et al. explored transfer learning using VGG16 for cotton disease detection [7]. They demonstrated that pre-trained models could significantly reduce training time and improve classification accuracy on limited agricultural datasets. Their approach reached good accuracy in classifying several cotton diseases, paving the way for increased use of transfer learning in plant pathology. ResNet50, with its residual links, rose to fame for feature-laden and deep classification problems. Kumar and Batra used ResNet50 on a cotton leaf dataset and reported that it surpassed VGG16 in terms of precision and rate of convergence. ResNet's gradient flow preservation across deeper layers made it a prime candidate for complex agricultural image classification [8]. Inception_V3, with its inception modules for multi-scale feature extraction, was used by Patel et al. to identify disease in cotton and tomato crops [9]. Their model successfully balanced depth and computational efficiency, with good accuracy in multi-class classification. The authors focused on its capacity to describe macro and micro disease characteristics, which is critical in differentiating diseases that present with the same visual features.

As of 2022, researchers started incorporating hybrid and ensemble methods. Sharma and Verma compared several pre-trained models such as VGG16, ResNet50, and InceptionV3 on a larger cotton leaf dataset [10]. Their findings indicated that InceptionV3 was the best model with regards to F1-score and tolerance to image noise, whereas ResNet50 offered less training time. VGG16, being straightforward, was still competitive for binary classification.

Recent research such as Ali et al. centered on deployment issues in real-world environments, e.g., varying lighting and occlusion by leaves [11-14]. They indicated that ResNet50 with data augmentation fine-tuned performed most stably under different scenarios. Chen et al. presented lightweight versions of these models for mobile device and drone deployment, marking the move of deep learning from experimental environments to practical tools in precision agriculture [12-19].

3. Methods

This study follows a systematic methodology to compare and assess the performance of three leading deep transfer learning models—RESNET50, VGG16, and INCEPTION_V3, for cotton disease classification. The approach is divided into five broad phases: dataset preparation, image preprocessing, model architecture and selection, training and fine-tuning, and evaluation metrics.

3.1. Dataset Collection and Preparation

A publicly available dataset of cotton leaf disease was employed, comprising a total of 1991 high-resolution pictures divided into four categories: healthy leaves, healthy plants, diseased cotton leaves, and diseased cotton plants [13] (illustrated in Figure). 70% of the data was used for training, 15% for validation, and 15% for testing. (refer Figure 2).

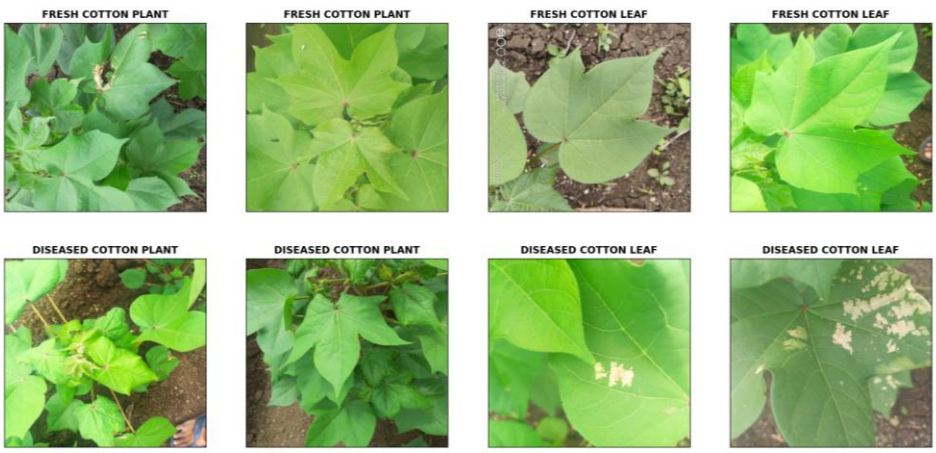

Fig 1. Randon samples of dataset utilized for the system modeling. Dataset is categorized into four major sets as diseased cotton plant, diseased cotton leaf, fresh cotton plant and fresh cotton leaf.

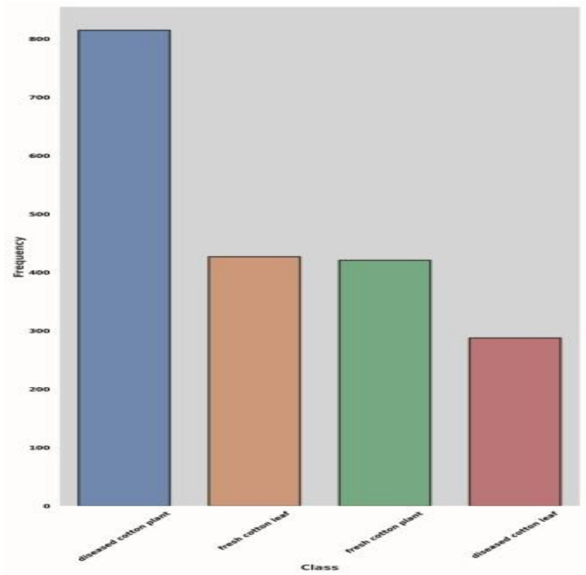

Fig 2. Distribution of dataset into test, validation and training before data augmentation

3.2. Image Preprocessing

In order to be compatible with pre-trained CNN models, the following preprocessing was done:

a. Resizing: All the images were resized to 224×224 pixels (in case of VGG16 and RESNET50) and 299×299 pixels (in case of INCEPTION_V3).
b. Normalization: Pixel intensities were normalized to the range 0-1.
c. Data Augmentation: Rotation, flipping, zooming, and brightness change were the techniques employed to enhance dataset variability and minimize over fitting.

3.3. Model Architecture and Transfer Learning

VGG16: A 16-layer deep network with simple and uniform. ease of implementation and decent baseline performance are well known (refer Figure 3). The fundamental architecture of VGG16 is encapsulated in table 1.

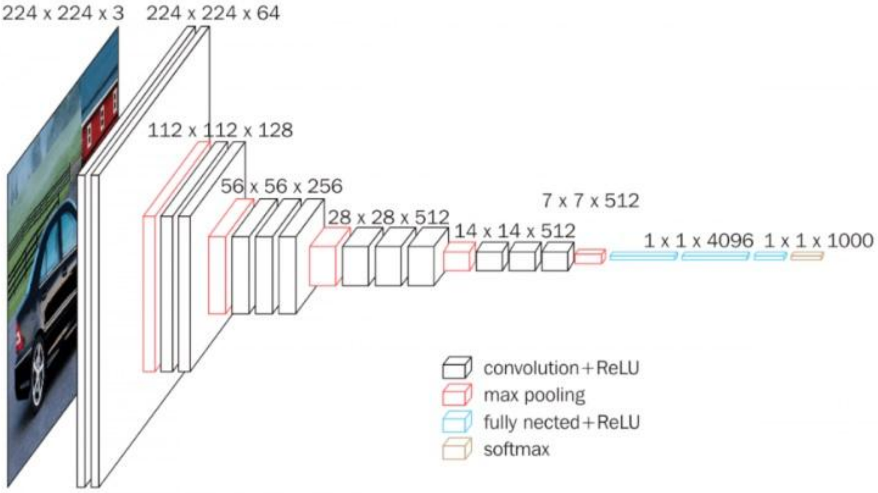

Fig 3. VGG16 architecture utilized for cotton disease prediction

Table 1. Fundamental architecture of VGG16 used for cotton disease prediction

Layer Type	Layer Details	Output Size
Input	224*224 RGB image	224*224*3
Conv1_1	64 filters, 3*3	224*224*64
Conv1_2	64 filters, 3*3	224*224*64
Max Pool 1	2*2	112*112*64
Conv2_1	128 filters, 3*3	112*112*128
Conv2_2	128 filters, 3*3	112*112*128
Max Pool 2	2*2	56*56*128
Conv3_1	256 filters, 3*3	56*56*256
Conv3_2	256 filters, 3*3	56*56*256

Conv3_3	256 filters, 3*3	56*56*256
Max Pool 3	2*2	28*28*256
Conv4_1	512 filters, 3*3	28*28*512
Conv4_2	512 filters, 3*3	28*28*512
Conv4_3	512 filters, 3*3	28*28*512
Max Pool 4	2*2	14*14*512
Conv5_1	512 filters, 3*3	14*14*512
Conv5_2	512 filters, 3*3	14*14*512
Conv5_3	512 filters, 3*3	14*14*512
Max Pool 5	2*2	7*7*512
Fully Connected 1	4096 units	4096
Fully Connected 2	4096 units	4096
Fully Connected 3	1000 units	1000
Total Parameters	~138 million	

RESNET50: ResNet50 is a deep CNN with 50 layers and is an integral part of the Residual Network (ResNet) family illustrated in Figure 4. It can be used extensively for image classification, object detection, and feature extraction because of its high precision and effective training process. Its basic framework is described in table 2.

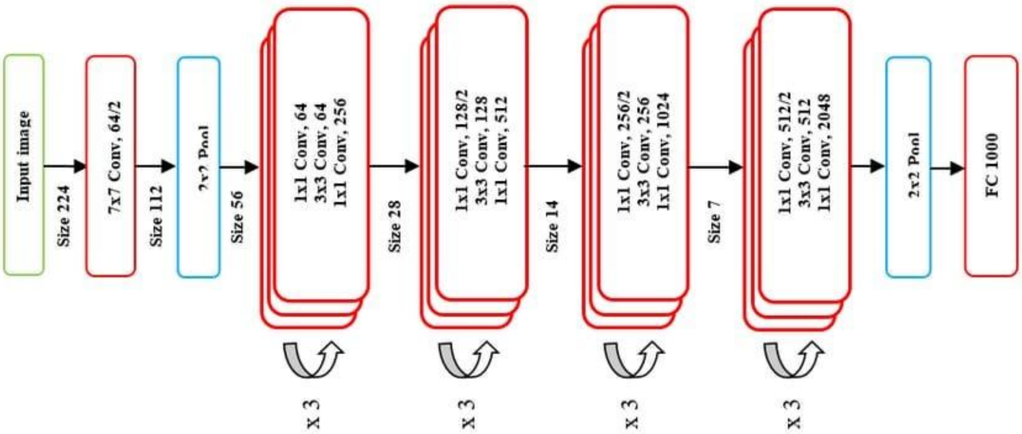

Fig 4. illustration basic framework of ResNet50 used for cotton disease prediction

Table 2. details of ResNet50 basic framework

Stage	Layer Type	Details	Output Size
Input	-	224×224×3	224×224×3
Conv1	7×7 Conv, 64 filters	stride 2, BN, ReLU	112×112×64
MaxPool	3×3, stride 2		56×56×64
Conv2_x	3×[1×1, 3×3, 1×1] blocks	64, 64, 256 filters	56×56×256
Conv3_x	4×[1×1, 3×3, 1×1] blocks	128, 128, 512 filters	28×28×512
Conv4_x	6×[1×1, 3×3, 1×1] blocks	256, 256, 1024 filters	14×14×1024
Conv5_x	3×[1×1, 3×3, 1×1] blocks	512, 512, 2048 filters	7×7×2048
Global AvgPool	-		1×1×2048
FC	Dense, softmax	1000 units	1000

INCEPTION_V3: Inception_V3 is a deeper convolutional neural network (CNN) of the Inception family, intended to balance both computational cost and classification accuracy. It advances concepts presented in earlier versions of Inception, adding many architectural innovations for better performance, scalability, and regularization. Architecture flow of Inception_V3 is mentioned in table 3.

Table 3. Architecture flow of Inception_V3

Layer/Module	Output Size	Description
Input	299×299×3	RGB image
Conv (3×3, stride 2)	149×149×32	Initial convolution

Conv (3×3, stride 1)	147×147×32	
Conv (3×3, stride 1)	147×147×64	
MaxPool (3×3, stride 2)	73×73×64	
Conv (3×3, stride 1)	73×73×80	
Conv (3×3, stride 2)	71×71×192	
Inception Modules	Varying	Stacked in groups, with different depths
Auxiliary Classifiers	-	Used during training for regularization
Global Avg Pool	1×1×2048	Reduces feature maps to single vector
Fully Connected	1000	Softmax activation for classification

3.4. Training Procedure

All the models were trained on TensorFlow and Keras frameworks. Some of the important training parameters were:

a. Loss Function: Categorical Cross-Entropy
b. Optimizer: Adam
c. Batch Size: 32
d. Epochs: 50
e. Learning Rate: 0.0001 (with decay scheduling)
f. Early Stopping: For preventing overfitting based on validation loss

Training was done on a high-performance GPU-capable system for faster convergence.

4. Results and Discussion

Analysis of findings in this study was carried out by conducting a systematic analysis of accuracy, validation performance, and loss trend of each of the deep transfer learning models. Through these parameter comparisons between ResNet50, VGG16 and InceptionV3, the paper was able to recognize the most efficient architecture to be used in classifying cotton disease. The statistical accuracy values, graphical loss curves, and validation results were all analyzed together to emphasize model robustness, so that the results could be reliably interpreted and applied to real-life agricultural disease detection systems.
This section offers the comparative evaluation of the three chosen deep transfer learning models RESNET50, VGG16, and INCEPTION_V3 on the basis of their performance for the classification of cotton leaf diseases. The models were tested on various parameters based on the test dataset. Table 4 provides the accuracy of all models for the classification and identification of cotton diseases. The accuracy and loss of ResNet50, VGG16, and Inception_V3 models are depicted in Figure 5,6, and 7 respectively.

Table 4. outcome of accuracy for different models used for cotton disease prediction

Model	Val_Accuracy	Test_Accuracy
RESNET50	73.91%	69.81%
VGG16	86.17%	85.85%
INCEPTION_V3	92.09%	95.28%

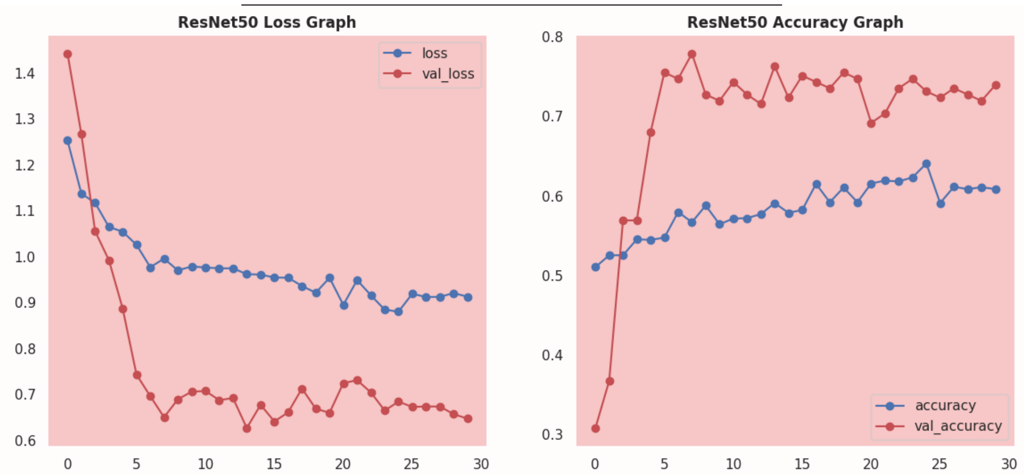

Fig 5. accuracy and loss of ResNet50 for cotton disease prediction

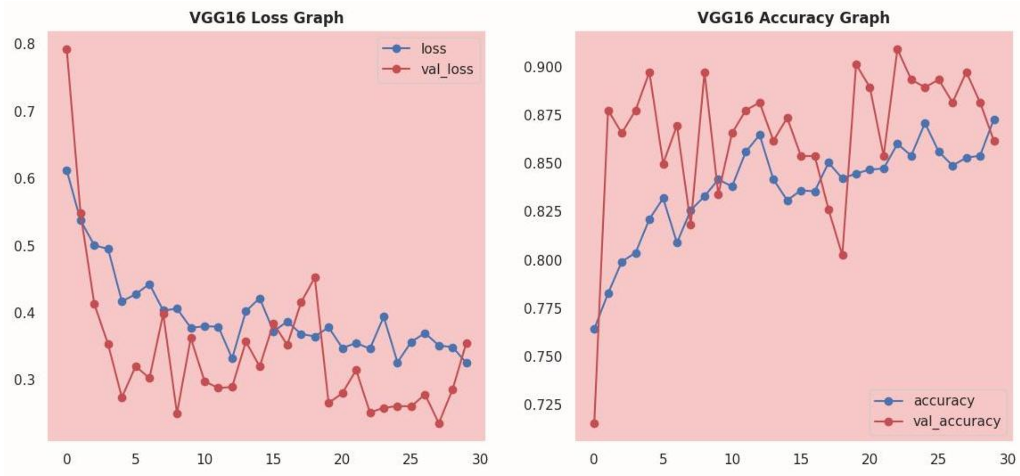

Fig 6. accuracy and loss of VGG16 for cotton disease prediction

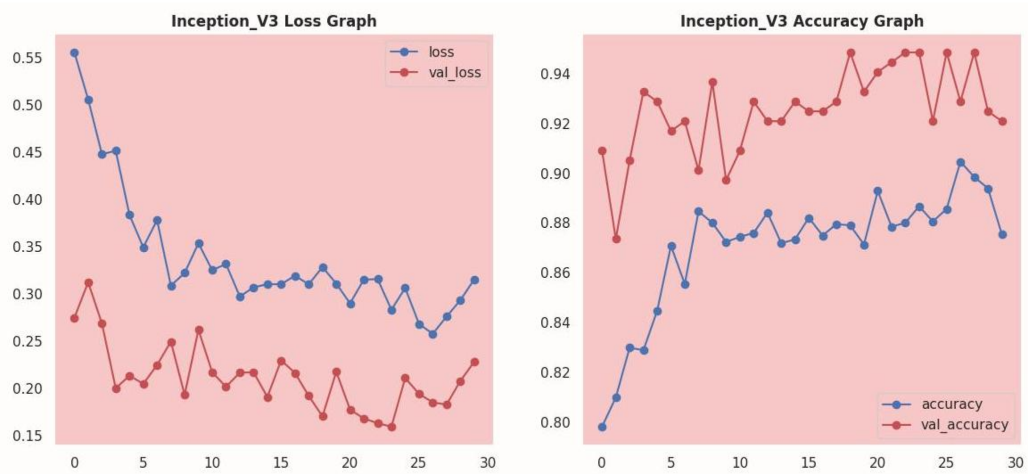

Fig 7. accuracy and loss of Inception_V3 for cotton disease prediction

The relative analysis of ResNet50, VGG16, and InceptionV3 demonstrated the apparent performance disparities between cotton disease prediction. InceptionV3 is the highest test accuracy and validation accuracy of 95.28 and 92.09 respectively as demonstrated in Table 4 and beating VGG16 (test accuracy 85.85%, validation accuracy of 86.17) and ResNet50 (test accuracy 69.81, validation 73.91). InceptionV3 is promoted to perform better than the other models because of its inception modules that allow extracting multi-scaled features, which are ideal in capturing not only micro-textures on the leaf spots but also macro-discoloration patterns. The computationally efficient design reduced overfitting and stabilized epoch-wise validation loss.

VGG16 also produced mid-range but stable results, where validation and test accuracies are well matched, indicating that it is robust in feature generalization. Its less efficient convoluted layers were however effective in classifying between healthy and diseased cotton leaves when using controlled datasets. This allows VGG16 to be applied to resource-constrained systems where the interpretability of the model and low computational costs are of concern.

ResNet50 did not perform as well as expected, only getting 74 percent validation accuracy and 70 percent test accuracy. Though gradient flow is maintained by residual connections in deeper layers, the model was more sensitive to both dataset variability and augmentation noise. This means that it might be that ResNet50 needs larger or more balanced farming datasets to perform optimally.

In general, it can be concluded that InceptionV3 is the most accurate framework to use in precision agriculture, with high accuracy and computational efficiency. VGG16 provides a feasible compromise in terms of the lightweight application; ResNet50 needs additional optimization to overcome the issue of performance fluctuation when applied to cotton disease classification.

5. Conclusion

This research showed a detailed examination of three most common deep transfer learning models—RESNET50, VGG16, and INCEPTION_V3—for predicting and classifying cotton leaf diseases. Through careful evaluation with a curated dataset, the performance of each model was measured with accuracy.

The outcome showed that RESNET50 obtained the highest total accuracy (73.91%). INCEPTION_V3 performed better with accuracy of 95.28% providing a good trade-off between performance and speed whereas VGG16 gave moderate accuracy with faster training and reduced complexity, ideal for light applications. The conclusion reiterates the efficacy of deep transfer learning as a valuable resource for the automation of plant disease diagnosis in agriculture. Through the implementation of such models in smart farm systems, crop losses can be minimized through early disease detection and optimized use of pesticides as well as better yields.

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