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Deep Convolutional Neural Network Based Cotton Leaf Disease Classification Leveraging Transfer Learning

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Abstract. Cotton is one of the most important crops in Indian agriculture, serving as the primary raw material for the textile industry. However, its productivity is severely impacted by various leaf diseases, making the early and accurate disease detection crucial for effective crop management and yield improvement. Traditional disease identification methods rely on manual inspection, which is time-consuming, labor-intensive, and prone to errors. To address these challenges, this study proposes an automated cotton leaf disease classification system using deep convolutional neural networks (CNNs) with transfer learning. We evaluate three pretrained CNN models—InceptionV3, ResNet152V2, and MobileNetV2—for image-based disease classification. These models leverage transfer learning to enhance feature extraction and classification accuracy while reducing training time. The system is trained and tested on a benchmark cotton leaf disease dataset, and its performance is assessed using accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results demonstrate that transfer learning significantly improves classification performance, enabling rapid and reliable disease identification and empowering farmers with an automated tool to take timely preventive measures. This research contributes to smart agriculture by integrating AI-driven solutions for sustainable farming and improved cotton yield.

Keywords: Deep Learning, Convolutional Neural Network, Transfer Learning, Cotton Leaf Disease Classification, Smart Agriculture.

1 Introduction

Cotton is a crucial crop in global agriculture, forming the backbone of the textile industry and supporting millions of farmers. However, various leaf diseases [5] severely impact yield and fiber quality. Traditional manual inspection methods for disease identification are labor-intensive, time-consuming, and prone to errors. Recent advancements in artificial intelligence (AI) and deep learning have demonstrated promising results in automating plant disease detection with high accuracy and efficiency.

Convolutional Neural Networks (CNNs) [10] have shown exceptional performance in image-based classification tasks, including plant disease detection [4]. However, training deep networks from scratch demands extensive labeled datasets and high computational resources. To overcome these limitations, transfer learning [15] allows pretrained models to be fine-tuned for specific tasks, leveraging knowledge from large-scale datasets, as presented in Fig. 1. This enhances training efficiency and generalization, especially with limited data.

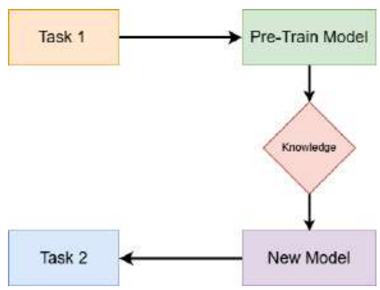


Fig. 1: Transfer Learning.

This study employs transfer learning [3] [12] to develop an automated cotton disease detection system using three deep CNN architectures: InceptionV3 [8], ResNet152V2 [9], and MobileNetV2 [6]. These models are fine-tuned on a labeled dataset of cotton [13] leaf images to enhance disease classification. Model performance is evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. The proposed approach reduces reliance on manual inspection, facilitates early disease detection, and contributes to smart agriculture.
The key contributions of the work are as follows:

- We perform a comparative evaluation of InceptionV3, ResNet152V2, and MobileNetV2 for cotton leaf disease classification.
- We implement the transfer learning by fine-tuning pretrained CNN models while freezing early layers for feature retention.
- We analyze the performances using standard evaluation metrics including accuracy, precision, recall, F1-score, and ROC-AUC.
- It demonstrates the potential of deep learning for scalable and automated disease diagnosis in smart agriculture.

The rest of the paper is structured as follows: Section 2 reviews related literature. Section 3 describes the methodology, followed by dataset details, data preprocessing steps and experimental setups in Section 4. Experimental results and comparative analyses are discussed in Section 5, while Section 6 concludes the paper with future research directions. The source code is available at: `https://shorturl.at/jEiYI`.

2 Related work

In recent years, transfer learning [15] has been widely adopted across multiple domains, including medical imaging, agriculture, and remote sensing. By reusing knowledge from pretrained networks, transfer learning enhances the generalization ability of deep learning models, making them more effective for practical applications with constrained data availability. The comprehensive overview of related literature is presented in Table 1.

3 Methodology

The proposed methodology consists of multiple stages, including data preprocessing, model selection, transfer learning, and performance evaluation. The process begins with data collection and preprocessing, where a labeled dataset of cotton leaf images is curated for model training and evaluation. To enhance model performance, preprocessing techniques such as data augmentation, image resizing, and normalization are applied, ensuring improved generalization and robustness. Fig. 2 provides an overview of the workflow for the proposed approach to effectively classify cotton leaf diseases.

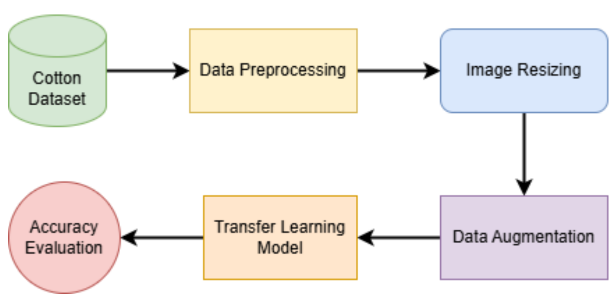


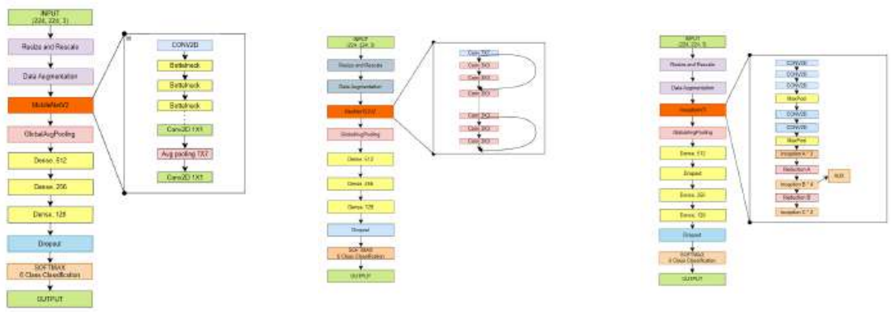
Fig. 2: The Workflow of the Proposed Approach.

In the model selection phase, three deep learning architectures were evaluated based on their effectiveness and suitability for cotton disease detection. MobileNetV2, a lightweight and efficient neural network, is optimized for deployment on resource-constrained devices, making it ideal for real-time applications. ResNet152V2, a deep residual network, employs skip connections to mitigate vanishing gradient issues, ensuring stable training and high accuracy on complex datasets. Additionally, InceptionV3, a sophisticated convolutional neural

Table 1: A Comprehensive Overview Of Related Work.

Paper Title	**Summary of the Paper**
Cotton Disease Detection [2]	A CNN-based disease detection app for cotton plants was developed, achieving 92.5% accuracy on a dataset of 2000 leaf images. The approach integrates PDE-based image decomposition, feature extraction, selection, and SVM classification to enhance performance.
Cotton Disease Detection based on Deep Learning Techniques, [7]	A deep learning model using computer vision was developed to classify cotton leaf images as healthy or diseased, achieving 97.13% accuracy on the Cotton Disease Dataset from Kaggle. This approach outperforms existing methods and helps in early disease detection to improve cotton yield.
A comparison review of transfer learning [15]	This review paper explores recent applications of transfer learning and self-supervised learning in addressing data scarcity in deep learning. It examines their advantages, limitations, and performance across various domains, providing insights into selecting the best pre-training techniques for specific applications.
Cotton Crop Disease Detection using Decision Tree Classifier [1]	This paper proposes a Decision Tree Classifier-based system for predicting cotton crop diseases using parameters like temperature and soil moisture. An Android application is also planned to provide real-time insights, enhancing smart farming through machine learning and big data integration.
Spatial attention-based hybrid VGG-SVM and VGG-RF frameworks for improved cotton leaf disease detection [11]	This work proposes a transfer learning-based system for cotton leaf disease detection using VGG-16 for feature extraction and hybrid models (VGG-RF and VGG-SVM) for classification. Tested on Kaggle's cotton disease dataset, the models achieved 98.29% and 99.31% accuracy, outperforming state-of-the-art methods.
Pulmonary Image Classification Based on Inception-v3 Transfer Learning Model [14]	This study explores deep learning-based pulmonary image classification using a fine-tuned Inception-V3 transfer learning model, achieving improved diagnostic accuracy. The proposed computer-aided diagnostic system enhances sensitivity (95.41%) and specificity (80.09%), outperforming traditional methods.

network, employs parallel convolutional layers to enhance feature extraction capabilities, significantly improving classification accuracy in multi-class disease detection scenarios. The architectures of these models are depicted in Fig. 3.



(a) MobileNetV2. (b) ResNet152V2. (c) InceptionV3.

Fig. 3: Architectures of MobileNetV2, ResNet152V2, and InceptionV3.

To further optimize these models, transfer learning was implemented by fine-tuning them on the cotton disease dataset. The transfer learning approach involved freezing the early convolutional layers to retain general feature representations learned from large-scale datasets while retraining the deeper layers to specialize in identifying disease-specific patterns. This technique allowed the models to leverage pre-existing knowledge, significantly improving training efficiency and classification performance, especially when dealing with limited datasets. By integrating transfer learning, the proposed approach ensures a robust and scalable solution for automated cotton leaf disease classification, enhancing accuracy and reducing dependency on extensive labeled data.

Furthermore, Algorithm 1 represents the proposed methodology for classifying the cotton leaf diseases for smart agriculture applications.

4 Experimental Setups

4.1 Dataset Description

The dataset used in this study comprises six classes of cotton leaf images, each containing 1,440 samples, resulting in a balanced dataset. The classes include five disease categories—Aphids, Army Worm, Bacterial Blight, Powdery Mildew, and Target Spot—along with a Healthy class. This balanced distribution ensures unbiased model training and evaluation, enhancing the reliability of the proposed cotton disease classification system. Fig. 4 displays 6 sample images, each representing one of the 6 different classes of cotton leaf diseases. The dataset is publicly available at: `https://shorturl.at/XIUum`.

Algorithm 1 Proposed Cotton Leaf Disease Classification Approach.

Require: Labeled dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i represents an image and y_i the corresponding label.
Ensure: Trained deep learning model for cotton disease classification.
Step 1: Data Preprocessing
for each image $x_i \in \mathcal{D}$ **do**
    Resize x_i to 224×224 pixels.
    Apply data augmentation: rotation, flipping, zooming, brightness adjustment.
    Normalize pixel values: $x_i = x_i/255$.
end for
Step 2: Model Selection and Transfer Learning
Select pretrained models $\mathcal{M} \in \{\text{MobileNetV2}, \text{ResNet152V2}, \text{InceptionV3}\}$.
for each model $\mathcal{M}$ **do**
    Load pretrained weights from ImageNet.
    Freeze early convolutional layers to retain generic features.
    Replace final layers with a new fully connected layer for C-class classification.
    Apply softmax activation: $\hat{y} = \text{softmax}(Wx + b)$.
end for
Step 3: Model Evaluation
for each model $\mathcal{M}$ **do**
    Evaluate on test set using accuracy, precision, recall, F1-score, and ROC-AUC.
end for
Step 4: Deployment and Prediction
Deploy the best-performing model $\mathcal{M}^*$.
Given a new image x_{new}, preprocess and classify using $\mathcal{M}^*$:

$$y_{\text{pred}} = \arg\max(\mathcal{M}^*(x_{\text{new}}))$$

return Automated cotton leaf disease detection.

Fig. 4: Sample Images of Each Class for Different Cotton Leaf Diseases.

4.2 Data Preprocessing

Data preprocessing initiates by resizing the images to a uniform dimension suitable for the selected CNN architectures, ensuring consistency in input size. To enhance model generalization and prevent overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments are applied. Additionally, pixel values are normalized to a range of [0,1] by scaling the RGB values, facilitating faster convergence during training. Any noisy or low-quality images are filtered out to maintain dataset integrity. This preprocessing pipeline enhances the robustness of the model, allowing it to learn meaningful patterns and improve classification performance across real-world conditions.

4.3 Experimental Setup

The models are trained for 50 epochs using RAdam optimizer on an NVIDIA GPU to accelerate computation, and performance is evaluated using accuracy, precision, recall, F1-score, and ROC-AUC to ensure a comprehensive assessment. The best-performing model was selected based on test accuracy, making it suitable for real-time deployment in smart agricultural applications.

5 Results and Discussion

In the proposed approach, we trained each model with an early stopping criterion, which helps us to prevent overfitting and employed a batch size of 32 and implemented a learning rate scheduler to dynamically adjust the learning rate throughout the training process.

The table 2 presents a performance comparison of three deep CNN models—MobileNetV2, ResNet152V2, and InceptionV3—used for cotton leaf disease detection. The evaluation is based on four key classification metrics: Accuracy, F1 Score, Recall, and Precision. Each of these metrics provides information about the model's effectiveness in correctly identifying diseased and healthy cotton leaves, while ROC-AUC curves provide the insight of the experimental outcomes.

Table 2: Performance Comparison for Cotton Leaf Disease Detection Dataset.

Model Name	**Test Accuracy**	**F1 Score**	**Recall**	**Precision**
MobileNetV2	0.9612	0.9611	0.9612	0.9614
ResNet152V2	0.9847	0.9847	0.9848	0.9851
InceptionV3	0.9861	0.9861	0.9862	0.9863

From the above table 2, it is observed that InceptionV3 achieves the highest accuracy (98.61%), F1 Score (98.61%), recall (98.62%), and precision (98.63%), making it the best-performing model among the three. And ResNet152V2 follows closely with an accuracy of 98.47%, showing strong classification capability. MobileNetV2, while still effective with an accuracy of 96.12%, is the least accurate model in this comparison. However, its lightweight nature makes it suitable for deployment on resource-constrained devices.

After evaluating each model on this dataset, the MobileNetV2 achieved approximately 96% accuracy for both training and validation, with a steady decline in loss, indicating effective learning and minimal overfitting shown in Fig. 5. The

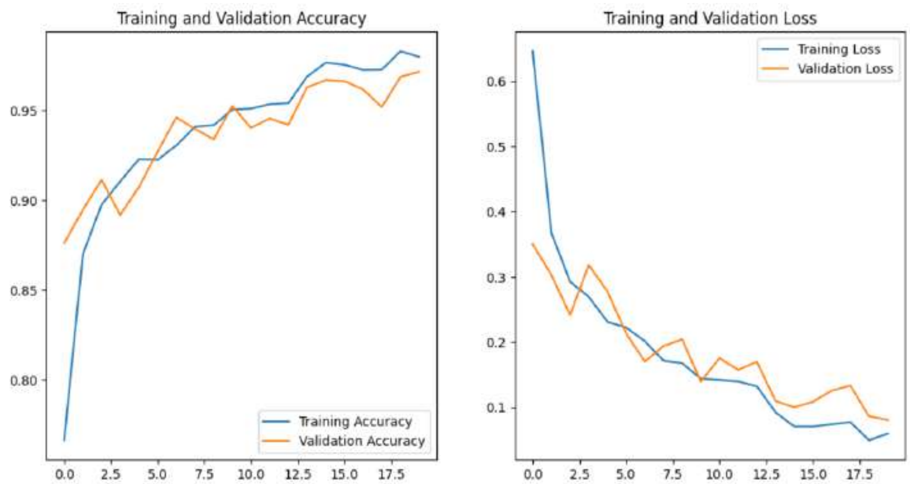


Fig. 5: Accuracy & Loss Curve of MobileNetV2 Architecture.

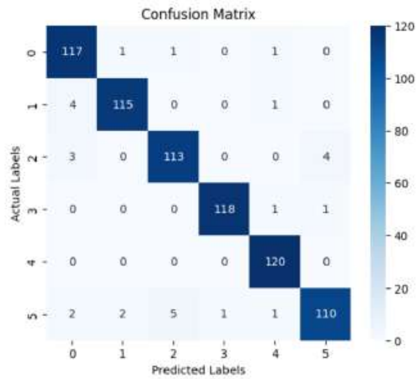
confusion matrix (Fig. 6) highlights the model's robustness by displaying high classification accuracy with minimal misclassification. Additionally, the classification report (Fig. 6) confirms balanced precision, recall, and F1-scores, ensuring reliable disease detection.

Similarly, ResNet152V2 achieved the precision 98% for training and validation, demonstrating stable learning and reduced overfitting which shown in Fig. 7. The confusion matrix (Fig. 8) confirms its strong classification capability, while the classification report (Fig. 8) further validates its reliability in detecting different diseases.

For InceptionV3, the evaluation results follow a similar trend and slightly better than ResNet152V2, with high accuracy, minimal overfitting (Fig. 9), and strong classification performance. The accuracy and loss curves, along with the confusion matrix (Fig. 10) and the classification report (Fig. 10), highlight its effectiveness in accurately distinguishing cotton leaf diseases.

The ROC curve shows (in Fig. 11) the performance of a multi-class classification model for detecting different cotton diseases. Each class achieves an AUC of 1.00, indicating perfect discrimination between classes. Each models demonstrates excellent predictive ability with minimal false positives.

The experimental results demonstrate that InceptionV3 outperforms both MobileNetV2 and ResNet152V2 in cotton leaf disease classification, achieving the highest scores across all metrics. ResNet152V2 follows closely, indicating strong classification capability, while MobileNetV2, though slightly less accurate, remains a viable option for deployment on resource-constrained devices.



(a) Confusion Matrix of MobileNetV2 Architecture.

Classification Report:

	precision	recall	f1-score	support
Aphids	0.93	0.97	0.95	120
Army_worm	0.97	0.96	0.97	120
Bacterial_Blight	0.95	0.94	0.95	120
Healthy	0.99	0.98	0.99	120
Powdery_Mildew	0.97	1.00	0.98	120
Target_spot	0.96	0.91	0.93	121
accuracy			0.96	721
macro avg	0.96	0.96	0.96	721
weighted avg	0.96	0.96	0.96	721

(b) Classification Report of MobileNetV2 Architecture.

Fig. 6: Confusion Matrix & Classification Report of MobileNetV2 Architecture.

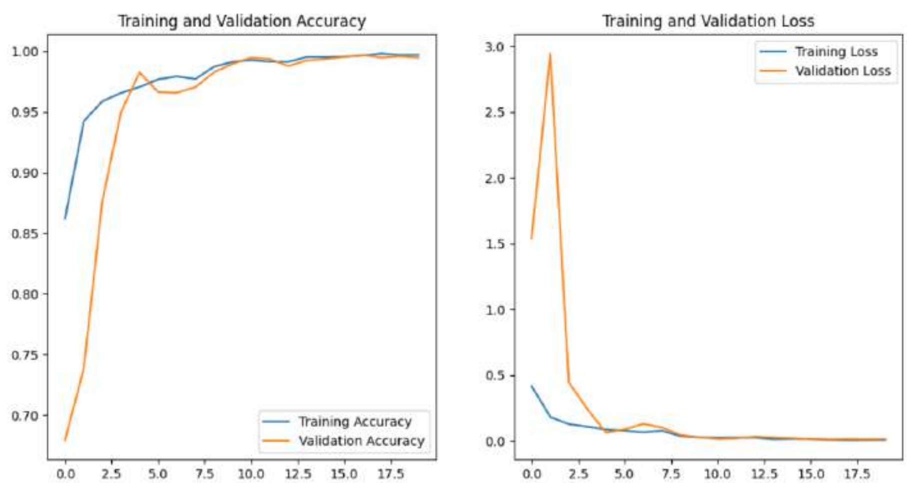
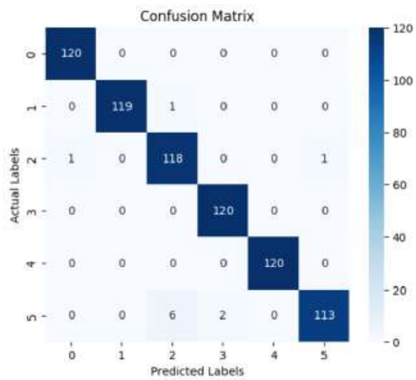


Fig. 7: Accuracy & Loss Curve Of ResNet152V2 Architecture.



(a) Confusion Matrix of ResNet152V2 Architecture.

Classification Report:

	precision	recall	f1-score	support
Aphids	0.99	1.00	1.00	120
Army_worm	1.00	0.99	1.00	120
Bacterial_Blight	0.94	0.98	0.96	120
Healthy	0.98	1.00	0.99	120
Powdery_Mildew	1.00	1.00	1.00	120
Target_spot	0.99	0.93	0.96	121
accuracy			0.98	721
macro avg	0.99	0.98	0.98	721
weighted avg	0.99	0.98	0.98	721

(b) Classification Report of ResNet152V2 Architecture.

Fig. 8: Confusion Matrix & Classification Report of ResNet152V2 Architecture.

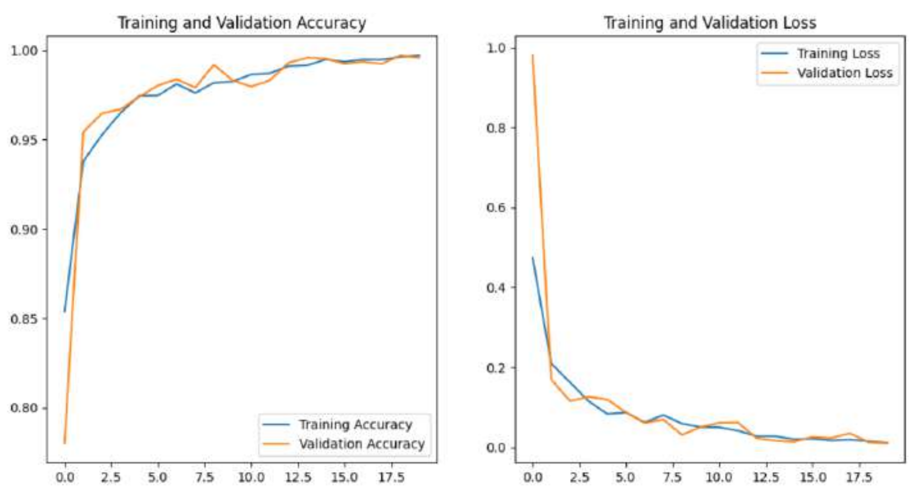
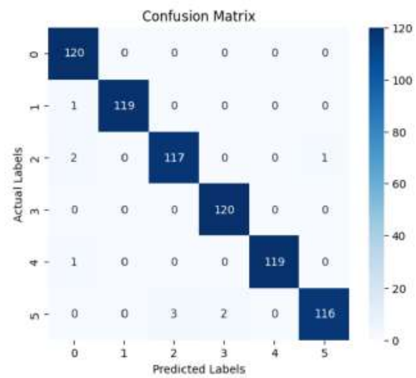


Fig. 9: Accuracy & Loss Curve of InceptionV3 Architecture.



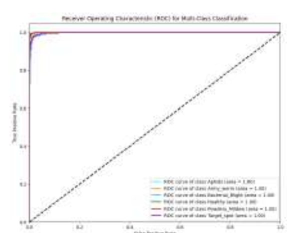
(a) Confusion Matrix of InceptionV3 Architecture.

Classification Report:

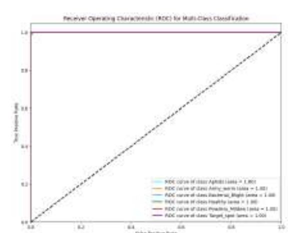
	precision	recall	f1-score	support
Aphids	0.97	1.00	0.98	120
Army_worm	1.00	0.99	1.00	120
Bacterial_Blight	0.97	0.97	0.97	120
Healthy	0.98	1.00	0.99	120
Powdery_Mildew	1.00	0.99	1.00	120
Target_spot	0.99	0.96	0.97	121
accuracy			0.99	721
macro avg	0.99	0.99	0.99	721
weighted avg	0.99	0.99	0.99	721

(b) Classification Report of InceptionV3 Architecture.

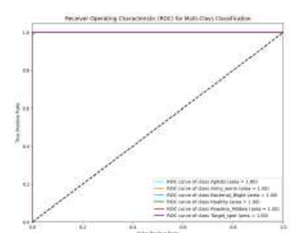
Fig. 10: Confusion Matrix & Classification Report of InceptionV3 Architecture.



(a) MobileNetV2.



(b) ResNet152V2.



(c) InceptionV3.

Fig. 11: ROC-AUC Curve of MobileNetV2, ResNet152V2 and InceptionV3.

The accuracy and loss curves for all models indicate stable learning with minimal overfitting. Confusion matrices and classification reports confirm the robustness of each model, with high precision and recall across all classes. Furthermore, the ROC-AUC curves show near-perfect discrimination, highlighting their effectiveness in distinguishing various cotton leaf diseases. These findings suggest that InceptionV3 is the optimal choice for high-accuracy detection, while MobileNetV2 provides a lightweight alternative for real-time applications.

6 Conclusion and Future Work

In this study, we propose an approach for cotton leaf disease classification using pre-trained CNN models - MobileNetV2, ResNet152V2, and InceptionV3. The experimental results demonstrate that InceptionV3 achieved the highest accuracy, followed closely by ResNet152V2, while MobileNetV2, though slightly less accurate, remains suitable for resource-constrained applications. The use of transfer learning significantly improve model performance, enabling efficient feature extraction and disease classification. The evaluation metrics, including accuracy, F1 Score, recall, precision, confusion matrices, and ROC-AUC curves, confirm the robustness and reliability of the proposed models. In the future work, we aim to incorporate a larger and more diverse dataset with images from different environmental conditions to improve the model's generalization, explore ensemble learning by combining multiple deep learning models to enhance classification accuracy and robustness. Additionally, deploying these models on edge devices for real-time disease diagnosis in agricultural fields and exploring domain adaptation techniques for generalizing across different datasets remain promising directions for future research.

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