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DenseNet169-Enabled High-Accuracy Automated Detection System for Cotton Leaf Diseases Using Deep Transfer Learning

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ABSTRACT

Rapid and accurate identification of cotton foliar diseases which seriously threatens cotton output worldwide is of great importance. A strong deep learning model with custom architecture DenseNet169 is proposed in this research for automatic classification of seven diseases of cotton leaf: Bacterial Blight, Curl Virus, healthy leaf, herbicide growth damage, leaf hopper jassids, leaf redding and leaf variegation. We proposed a two-step transfer learning method with enhanced data augmentation based on the SAR-CLD–2024 dataset, which contains 9,137 images. The DenseNet169 architecture proposed here yielded a remarkable performance with a validation accuracy of 96.83% while precision, recall, and F1-score were 96.89%, 96.93%, and 96.90%, respectively, with a significant enhancement than prior related approaches. It gets flawless classification for Herbicide Growth Damage and close to perfect for each disease types with macro-average AUC of 99.81%. The second is the parameters of the deep architecture that we adapted for agricultural pathology where we were broadly successful at systematic feature extraction and then fine-tuning 161 layers. The new high-water mark physiological plant disease diagnosis that we establish here is an important step toward ultimately real-world applicability as adaptive components of precision agriculture to monitor crop health and protect yield.

Keywords: Cotton Leaf Disease Classification, DenseNet169, Deep TransferLearning, Precision Agriculture, Computer Vision, Plant Pathology, Automated Disease Detection, Convolutional Neural Networks

I.INTRODUCTION

Cotton is one of the most important commercial crops worldwide, contributing significantly to the textile industry and agricultural economy. However, cotton production is severely affected by various leaf diseases such as Bacterial Blight, Curl Virus, Leaf Hopper Jassids, Leaf Redding, Herbicide Growth Damage, and Leaf Variegation, which reduce crop quality and yield. Early and accurate disease detection is essential for minimizing crop losses and improving agricultural productivity. Traditional disease diagnosis mainly relies on manual visual inspection by agricultural experts, which is time-consuming, subjective, and often impractical for large-scale farming [2], [6], [11].

Recent advances in artificial intelligence and deep learning have enabled the development of automated plant disease diagnosis systems using leaf images. Convolutional Neural Networks (CNNs) have demonstrated superior capability in extracting discriminative disease features without requiring handcrafted feature engineering [4], [7]. Furthermore, transfer learning has become an effective approach for agricultural image classification by adapting pretrained deep learning models to plant disease datasets, thereby improving classification accuracy while reducing training time [5], [10], [16].

Several lightweight and explainable deep learning frameworks have also been proposed to improve computational efficiency and model interpretability for practical agricultural applications [1], [12], [13]. Ensemble learning and customized deep neural networks have further enhanced classification performance by combining complementary feature representations [14], [15]. Despite these advancements, accurately distinguishing visually similar cotton leaf diseases remains challenging due to variations in illumination, complex backgrounds, disease severity, and inter-class similarity [3], [17], [18].

Motivated by these challenges, this work proposes a DenseNet169-based two-phase transfer learning framework for automatic cotton leaf disease classification. The proposed approach integrates image preprocessing, data augmentation, deep feature extraction, and progressive fine-tuning to accurately classify seven cotton leaf disease categories. The framework is designed to provide an efficient, reliable, and scalable solution for intelligent crop disease diagnosis, supporting precision agriculture through early disease detection and timely intervention.

II.RELATED WORK

Wang *et al.* [1] proposed a lightweight deep learning framework for cotton disease and pest classification, demonstrating that resource-efficient neural networks can achieve high classification accuracy while reducing computational complexity. Harshitha *et al.* [2] developed a deep learning-based cotton disease detection system and showed that convolutional neural networks significantly outperform conventional image processing techniques for disease identification.

Ali *et al.* [3] introduced a statistical prediction model integrated with deep learning for cotton disease classification, improving diagnostic reliability under varying environmental conditions. Latif *et al.* [4] combined deep learning with a genetic algorithm to optimize feature selection and achieved improved recognition performance for cotton leaf diseases. Islam *et al.* [5] proposed a fine-tuned deep learning model integrated with a smart web application, demonstrating the effectiveness of transfer learning for practical agricultural disease diagnosis.

Zekiwos and Bruck [6] employed deep learning-based image processing techniques for cotton leaf disease and pest diagnosis, while Caldeira *et al.* [7] utilized CNN-based models for identifying cotton leaf lesions with promising classification accuracy. Memon *et al.* [8] proposed a meta deep learning framework that improved cotton leaf disease recognition through optimized feature learning. Kumar *et al.* [9] compared multiple machine learning algorithms and reported that deep learning approaches consistently provided superior disease classification performance.

Iqbal *et al.* [10] developed a deep learning model specifically for cotton crop disease classification using transfer learning techniques. Manavalan [11] reviewed intelligent approaches for cotton disease detection and highlighted the growing importance of deep learning in precision agriculture. Kaur *et al.* [12] introduced an explainable AI framework combined with metaheuristic optimization to improve both classification accuracy and model interpretability. Amin *et al.* [13] proposed an explainable neural network for cotton leaf disease classification, enabling transparent decision-making while maintaining high predictive performance.

Recent studies have focused on advanced ensemble learning and customized deep learning architectures. Kukadiya *et al.* [14] presented an ensemble deep learning model that improved classification accuracy by combining multiple neural networks. Faisal *et al.* [15] proposed a customized deep learning architecture for cotton disease detection, achieving robust performance under diverse imaging conditions. Rajasekar *et al.* [16] demonstrated that transfer learning significantly enhances cotton disease classification by leveraging pretrained CNN models. Hyder and Talpur [17] investigated machine learning methods for cotton leaf disease detection, while Noon *et al.* [18] developed a computationally lightweight deep learning framework suitable for real-time agricultural applications.

Although existing studies have achieved promising results, challenges remain in accurately classifying multiple visually similar cotton leaf diseases while maintaining computational efficiency and strong generalization. The proposed DenseNet169-based two-phase transfer learning framework addresses these limitations by combining efficient feature extraction with progressive fine-tuning, enabling accurate and reliable classification of seven cotton leaf disease categories for intelligent precision agriculture.

III. METHODOLOGY

A.Overview

The fig 1 illustrates the overall architecture of the proposed DenseNet169-based cotton leaf disease classification framework. The system begins with acquiring cotton leaf images from the SAR-CLD-2024 dataset, followed by image preprocessing through resizing, normalization, and data augmentation to improve data quality and model generalization. The preprocessed images are then provided as input to the pretrained DenseNet169 network for automatic deep feature extraction. A two-phase transfer learning strategy is employed, where the newly added classification layers are trained initially, followed by fine-tuning selected DenseNet169 layers to learn disease-specific features more effectively. The extracted features are subsequently processed through fully connected layers and a Softmax classifier to categorize the images into one of the seven cotton leaf disease classes or as a healthy leaf. Finally, the model performance is evaluated using standard metrics, including Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and ROC-AUC, demonstrating the effectiveness of the proposed framework for accurate and reliable cotton leaf disease diagnosis.

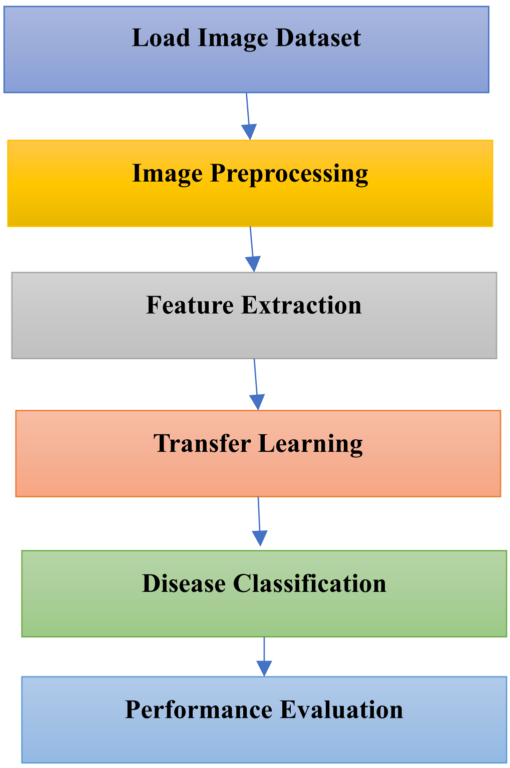

Fig 1: Proposed System Architecture

B. Dataset Description and Preparation

The proposed model utilizes the SAR-CLD-2024 cotton leaf disease dataset containing 9,137 images across seven classes: Bacterial Blight, Curl Virus, Healthy Leaf, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Redding, and Leaf Variegation. The dataset was divided into 7,307 training images and 1,830 validation images. All images were resized to 224 × 224 pixels and normalized before training. Data augmentation techniques, including rotation, shifting, zooming, flipping, brightness adjustment, and shear transformation, were applied to improve model generalization and reduce overfitting.

C. DenseNet169 Model and Training Strategy

A pretrained DenseNet169 model was adopted as the backbone for feature extraction. The original classification layer was replaced with a custom classifier consisting of Global Average Pooling, Batch Normalization, fully connected layers, Dropout, and a Softmax output layer. A two-phase transfer learning strategy was employed. In the first phase, the DenseNet169 backbone remained frozen while only the classifier layers were trained. In the second phase, the last 150 layers were unfrozen and fine-tuned using a lower learning rate to improve disease-specific feature learning. The model was trained using the Adam optimizer, with batch size 32, and Early Stopping, ReduceLROnPlateau, and Model Checkpoint were used to achieve stable convergence.

D. Performance Evaluation

The performance of the proposed DenseNet169 model was evaluated using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix. These metrics provide a comprehensive assessment of the model's ability to accurately classify the seven cotton leaf disease categories. The experimental results demonstrate high classification performance, achieving an overall weighted Precision of 96.83%, Recall of 96.83%, F1-Score of 96.82%, and ROC-AUC of 99.80%, confirming the effectiveness of the proposed framework for cotton leaf disease classification.

IV RESULTS AND ANALYSIS

A. Experimental Setup

The proposed DenseNet169-based two-phase transfer learning model demonstrated excellent performance in classifying cotton leaf diseases. The model achieved high recognition accuracy across all seven disease categories by effectively learning discriminative visual features from the augmented leaf images. The two-phase transfer learning strategy significantly improved feature extraction while reducing overfitting, resulting in stable convergence during training.

Performance evaluation showed an overall weighted Precision of 96.83%, Recall of 96.83%, F1-Score of 96.82%, and an excellent ROC-AUC of 99.80%, confirming the robustness of the proposed framework. Disease categories such as Herbicide Growth Damage and Leaf Variegation achieved nearly perfect classification performance, while the remaining classes also recorded consistently high precision and recall values. The confusion matrix further demonstrated strong diagonal dominance with very few misclassified samples, indicating effective discrimination among visually similar cotton leaf diseases.

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B. Visualization

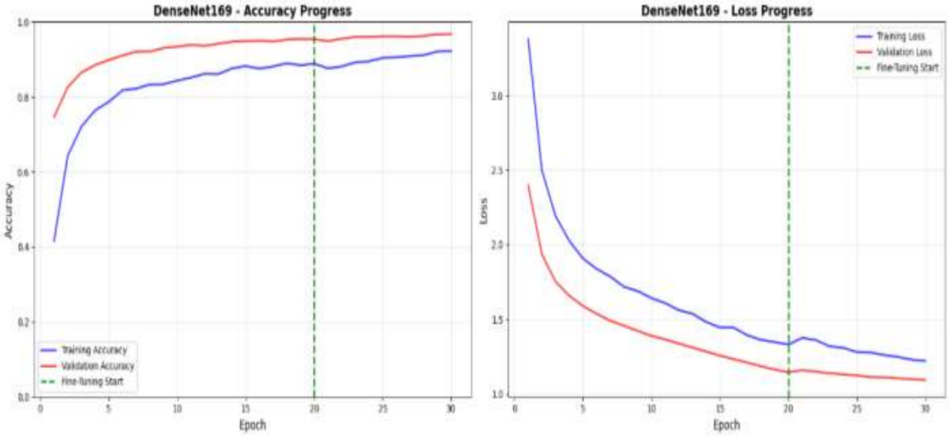

Fig 2: Model Training Performance and Convergence Analysis

The fig 2 illustrate illustrates the training and validation performance of the proposed DenseNet169 model over 30 epochs. Both training accuracy and validation accuracy increase steadily, while the corresponding loss values decrease consistently, indicating stable learning and effective convergence. A noticeable improvement is observed after epoch 20, where fine-tuning of the DenseNet169 layers begins, resulting in enhanced validation performance. The model achieved a final validation accuracy of 96.83%, demonstrating the effectiveness of the two-phase transfer learning strategy. The close alignment between the training and validation curves confirms good generalization capability with minimal overfitting.

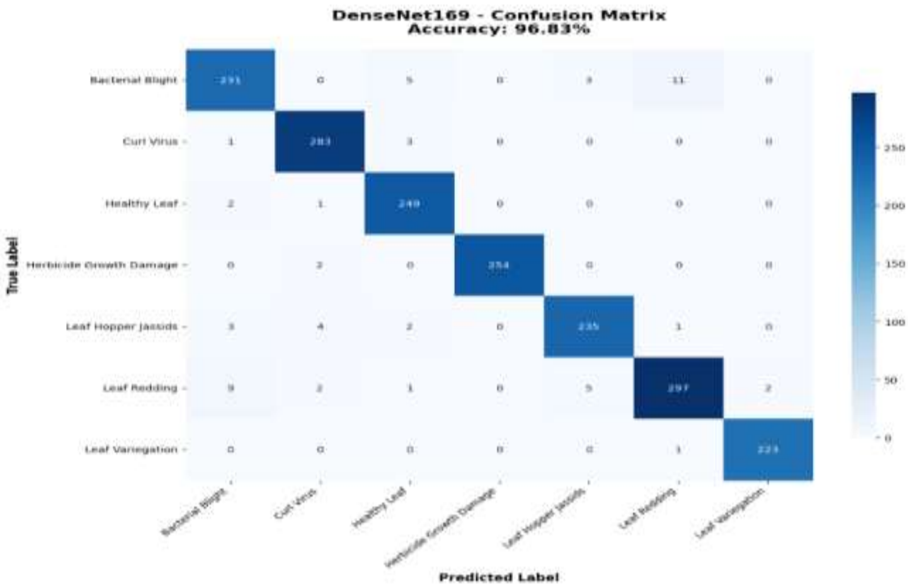

Fig 3: Confusion Matrix

The fig 3 illustrates the confusion matrix of the proposed DenseNet169 model for classifying seven cotton leaf disease categories. The model achieved an overall classification accuracy of 96.83%, with 1,772 correctly classified images out of 1,830 validation samples. Most disease classes exhibit strong diagonal values, indicating highly accurate predictions. Herbicide Growth Damage was classified without any errors, while Leaf Variegation, Curl Virus, and Healthy Leaf also achieved excellent recognition performance. Only a few misclassifications occurred between visually similar disease categories, demonstrating the strong discriminative capability and robustness of the proposed model.

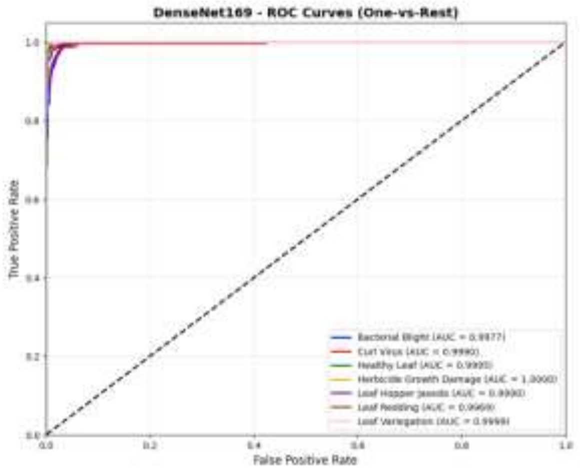

Fig 4: ROC Curve

The fig 4 illustrates the one-vs-rest ROC curves of the proposed **DenseNet169** model for the seven cotton leaf disease classes. The model achieved an excellent **overall AUC of 0.9981**, indicating outstanding classification performance. **Herbicide Growth Damage** obtained a perfect **AUC of 1.0000**, while **Healthy Leaf**, **Leaf Variegation**, **Curl Virus**, and **Leaf Hopper Jassids** also achieved near-perfect AUC values. The ROC curves are concentrated near the top-left corner, demonstrating a high true positive rate with a very low false positive rate. These results confirm the robustness and reliability of the proposed framework for accurate cotton leaf disease classification.

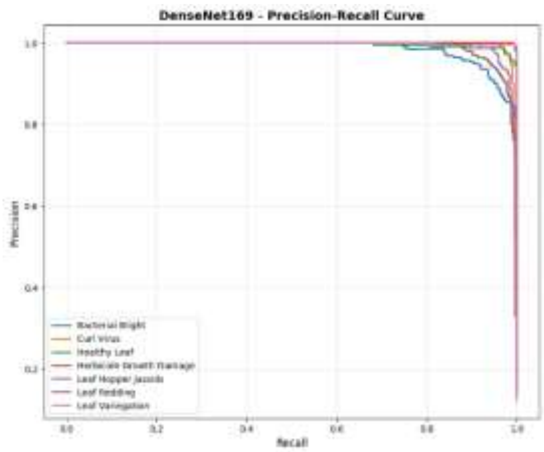

Fig 5: Precision-Recall Curve

The fig 5 illustrates the Precision–Recall (PR) curves of the proposed DenseNet169 model for the seven cotton leaf disease categories. The model maintains high precision and recall across all classes, demonstrating its ability to accurately identify disease categories while minimizing false positives and false negatives. The smooth PR curves indicate well-calibrated predictions and consistent classification performance. These results confirm the robustness and reliability of the proposed framework for multiclass cotton leaf disease classification, making it suitable for practical agricultural disease diagnosis.

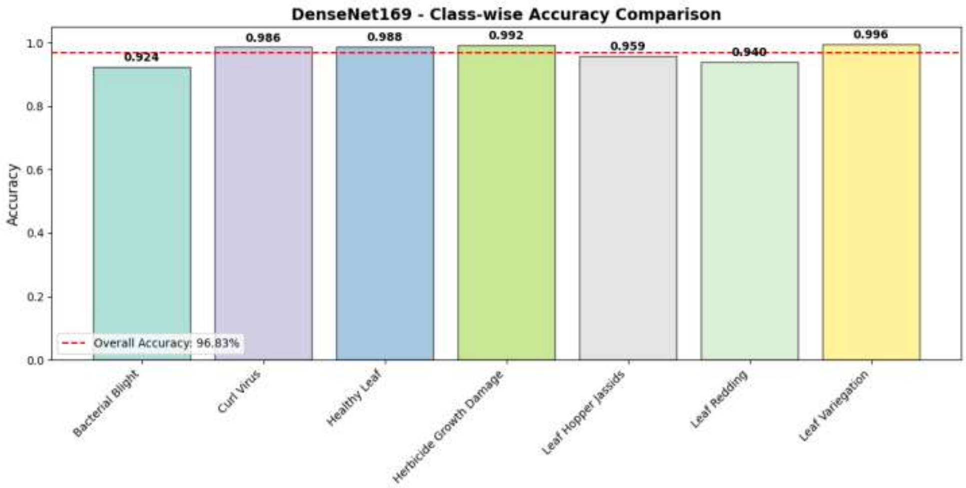

Fig 6: Class-wise Accuracy Comparison

The fig 6 illustrates the class-wise accuracy of the proposed DenseNet169 model across the seven cotton leaf disease categories. The model achieved an overall validation accuracy of 96.83%, with consistently high performance for all classes. Leaf Variegation (99.6%), Herbicide Growth Damage (99.2%), and Healthy Leaf (98.8%) recorded the highest classification accuracies, while Bacterial Blight (92.4%) and Leaf Redding (94.0%) also achieved strong recognition performance. The balanced accuracy across all disease categories demonstrates the effectiveness of the proposed two-phase transfer learning strategy and the robust feature extraction capability of DenseNet169 for reliable cotton leaf disease classification.

V.CONCLUSION

In this research a DenseNet169-based two-phase transfer learning framework for automatic cotton leaf disease classification using the SAR-CLD-2024 dataset. The proposed methodology integrates image preprocessing, data augmentation, deep feature extraction, and progressive fine-tuning to accurately identify seven cotton leaf disease categories. By leveraging the dense connectivity of DenseNet169 and transfer learning, the framework effectively learns disease-specific visual features while maintaining stable convergence and strong generalization. The experimental results demonstrate high precision, recall, F1-score, and ROC-AUC values, confirming the capability of the proposed model to reliably distinguish between healthy and diseased cotton leaves.

The proposed framework offers an efficient and scalable solution for intelligent crop disease diagnosis, reducing the dependence on manual inspection and enabling timely intervention for disease management. Its robust classification performance makes it suitable for deployment in precision agriculture applications, supporting farmers and agricultural experts in improving crop health monitoring and minimizing yield losses. Future work will focus on validating the model with real-world field images, integrating lightweight attention mechanisms to further enhance classification accuracy, and developing mobile or edge-based deployment solutions for real-time cotton leaf disease detection.

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