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Research Paper

A Lightweight Hybrid Deep Feature and Discriminant Learning Framework for Early Cotton Disease Diagnosis

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ABSTRACT

Recent studies report that cotton leaf diseases lead to yield losses of up to 30–40% when not detected at early stages, while automated vision-based systems achieve diagnosis accuracy exceeding 90% compared to manual inspection. Despite these advancements, existing models exhibit limitations such as reduced class-wise recall and high computational complexity when handling subtle early-stage symptoms. The motivation of this work is to develop an accurate, reliable, and efficient system for early cotton disease detection to support timely intervention and improve agricultural productivity. Manual diagnosis depends heavily on expert knowledge and remains time-consuming, subjective, and inconsistent under varying environmental conditions, while early symptoms often remain visually indistinguishable, leading to delayed treatment. To overcome these challenges, a lightweight Convolutional Neural Network (CNN)-based ensemble framework is proposed for early-stage cotton disease classification. A curated cotton leaf dataset comprising multiple disease categories and healthy samples is pre-processed and divided into training and testing sets to ensure unbiased evaluation. Baseline comparisons are conducted using Bagging, Light Gradient Boosting Machine (LGBM), and a CNN–Random Forest (RF) hybrid model. The proposed framework utilizes ResNet-50 for deep feature extraction, capturing both low-level texture and high-level disease-specific patterns, followed by Linear Discriminant Analysis (LDA) for classification to enhance class separability. Experimental results demonstrate that the ResNet-50 with LDA model achieves superior accuracy, precision, recall, and improved class-wise discrimination, particularly for early-stage diseases such as Aphids, Army worm, Bacteria blight, Powdery mildew, and Target spot. The lightweight architecture also reduces computational cost and inference time, ensuring suitability for real-time deployment in resource-constrained agricultural environments.

Keywords: Cotton Leaf Disease Detection, Convolutional Neural Network, ResNet-50, Deep Learning, Agricultural IoT.

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1. INTRODUCTION

Cotton plays a vital role in global agriculture, serving as a cornerstone of the textile industry and supporting the livelihoods of millions of farmers, particularly in regions such as Central Asia, South Asia, and parts of Africa. Despite its economic importance, cotton cultivation is highly vulnerable to a broad spectrum of biotic stressors, including foliar and vascular diseases such as leaf spot, fusarium wilt, gray mold, and aphid-induced stress]. These diseases can initiate at early developmental stages, subtly manifesting through visual symptoms like minor chlorosis, spot formation, and edge curling. If undetected and unmanaged, such conditions can escalate rapidly, leading to substantial yield losses and increased dependency on chemical pesticide. The timely detection of these early-stage symptoms is crucial for implementing effective integrated pest management (IPM) strategies. However, traditional methods such as manual scouting are labour-intensive, prone to human error, and lack scalability. Recent advancements in remote sensing technologies and deep learning-based image analysis have shown promise in automating disease detection tasks. Figure 1 illustrates the trends in cotton area, production, and yield from the 2019/20 crop year to the projected 2025/26 period. The cotton area, represented by the blue line, shows a gradual decline from 13.5 million hectares in 2019/20 to 11.5 million hectares in 2024/25, with a further slight decrease projected to 11.2 million hectares in 2025/26. Production, shown in red, decreased from 28.2 million 480 lb. bales in 2019/20 to 24.0 million bales in 2024/25 and is expected to slightly rise to 24.5 million bales in 2025/26. Meanwhile, yield, indicated by the green line, initially decreased from 455 kilograms per hectare in 2019/20 to 430 in 2021/22, then showed an upward trend, reaching 454 kg/ha in 2024/25 and a forecasted increase to 476 kg/ha in 2025/26.

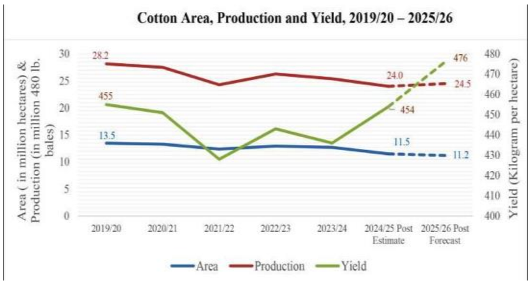

Fig. 1: Cotton area, production and yield.

Finally, Fig. 1 highlights a consistent reduction in the cotton-growing area over the analysed period, while production exhibits a more moderate decline, reflecting compensatory increases in yield. The yield trend indicates improved productivity per hectare, particularly in the post-estimate and forecast periods, suggesting that technological improvements, better crop management practices, or favourable conditions may be contributing to higher cotton efficiency despite a shrinking cultivation area. This divergence between area and yield underlines the importance of enhancing per-hectare productivity to maintain stable production levels.

2. LITERATURE SURVEY

Zhengle Wang et al. [1] proposed a lightweight model, the Resource-efficient Cotton Network (RF-Cott-Net), alongside an open-source image dataset, CCDPHD-11, encompassing 11 disease categories. Built upon the MobileViTv2 backbone, RF-Cott-Net integrates an early exit mechanism and quantization-aware training (QAT) to enhance deployment efficiency without sacrificing accuracy. Experimental results on CCDPHD-11 demonstrate that RF-Cott-Net achieves an accuracy of 98.4%, an F1-score of 98.4%, a precision of 98.5%, and a recall of 98.3%. Halimjon Khujamatov et al. [2] proposed model integrates an EfficientNetV2-S backbone with a Dual-Attention Feature Pyramid Network (DA-FPN) and a novel Early Symptom Emphasis Module (ESEM) to enhance sensitivity to subtle visual cues such as chlorosis, minor lesions, and texture irregularities. A custom-labeled dataset was collected from cotton fields in Uzbekistan to evaluate the model under realistic agricultural conditions. CottoNet achieved a mean average precision (mAP@50) of 89.7%, an F1 score of 88.2%, and an early detection accuracy (EDA) of 91.5%, outperforming existing lightweight models while maintaining real-time inference speed on embedded devices.

Hafiz Muhammad Faisal et al. [3] This study presented dissimilar state-of-the-art deep learning models for disease recognition including VGG16, DenseNet, EfficientNet, InceptionV3, MobileNet, NasNet, and ResNet models. For this purpose, real cotton disease data is collected from fields and preprocessed using different well-known techniques before being used as input to deep learning models. Experimental analysis reveals that the

ResNet152 model outperforms all other deep learning models, making it a practical and efficient approach for cotton disease recognition. Zhi-Yu Yang et al. [4] This review highlighted DL applications in seed quality assessment, pest and disease detection, intelligent irrigation, autonomous harvesting, and fiber classification et al. DL enhances accuracy, efficiency, and adaptability, promoting the modernization of cotton production and precision agriculture. However, challenges remain, including limited model generalization, high computational demands, environmental adaptability issues, and costly data annotation.

Swetha G et al. [5] They proposed CNN architecture employs a series of convolutional layers with reduced parameters, leveraging techniques such as depth-wise separable convolutions and global average pooling to maintain high performance while minimizing computational costs. They trained and validated our model on a comprehensive dataset comprising various cotton leaf diseases, including bacterial blight, leaf spot, and mildew. Wenzhong Yang et al. [6] They introduced the innovatively designed Reception Field Space Channel (RFSC) module to replace traditional convolution kernels. This module combines dynamic receptive field features with traditional convolutional features to effectively utilize spatial channel attention, helping CANnet capture local and global features of images more comprehensively, thereby enhancing the expressive power of features. At the same time, the module also solves the problem of parameter sharing.

Peipei Chen et al. [7] This addressed the issues of data imbalance. The model's effectiveness was further augmented by employing integration strategies such as relative majority voting, simple averaging, and weighted averaging. Our experimental results indicated significant accuracy improvements in the enhanced ResNet101, MobileNetV2, and DenseNet121 models by 2.3%, 2.91%, and 2.93%, respectively. Notably, the integration of these models consistently improved accuracy, with gains of 0.87% and 1.73% compared to the highest-performing single model, DenseNet121FC. Saleh Albahli et al. [8] Their proposed framework offered a scalable, practical solution for real-time crop health monitoring, contributing toward smart and sustainable agricultural ecosystems. Chetanpal Singh et al. [9] This approach started with image pre-processing, which they pass to a BERT-like encoder after linearly embedding the image patches. It results in segregating disease regions. Then, the output of the encoded feature is passed to ResNet-based architecture for feature extraction and further optimized by PSO to increase the classification accuracy.

Shangyun Jia et al. [10] They introduced Local Perception Unit (LPU) and Lightweight Multi-Head Self-Attention (LMHSA) modules were introduced to synergistically enhance the extraction of fine-grained plant disease details and model global dependency relationships, respectively. Second, an Inverted Residual Feed-Forward Network (IRFFN) was employed to optimize the feature propagation path, thereby enhancing the model's robustness against interferences such as lighting variations and leaf occlusions.

Muhammad Mahmood et al. [11] This review examined the most recent state-of-the-art techniques, datasets, and difficulties related to these crops' CNN-based disease detection systems. Firstly, we present a summary of CNN architecture and its applicability to classify tasks based on images. Subsequently, we explore CNN applications in the identification of diseases in vegetable crops, emphasizing relevant research, datasets, and performance measures. Rhea Patel et al. [12] In this review, they focus on the advances in the detection techniques, mainly the miniaturized systems that have developed in the last decade. The analytical techniques for plant pathogen detection have been classified as direct and indirect detection methods. The direct methods involving laboratory techniques such as polymerase chain reaction, enzyme-linked immune-sorbent assays, and immunofluorescence and their recent advances have been discussed.

Lijun Gao et al. [13] This module integrated multi-scale semantic information through a lightweight, multi-branch convolutional structure, enhancing the model's ability to detect small-scale lesions. To further overcome the receptive field limitations of traditional convolution, we propose incorporating a deformable attention transformer (DAT) into the C2PSA module. Haoran Feng et al. [14] This research is introduced to address the challenges of detecting cotton pests and diseases in natural environments, as well as the similarities in the features exhibited by cotton pests and diseases, a Lightweight Cotton Disease Detection in Natural Environment (LCDDN-YOLO) algorithm is proposed. The LCDDN-YOLO algorithm is based on YOLOv8n and replaces part of the convolutional layers in the backbone network with Distributed Shift Convolution (DSConv). Thandiwe Nyawose et al. [15] introduced recent architectures such as GreenViT, hybrid ViT–CNN models, and YOLO-based single- and two-stage detectors, comparing their accuracy, inference speed, and hardware efficiency. This review discusses multimodal and self-supervised learning techniques to enhance detection in complex environments, highlighting key limitations, including reliance on handcrafted features, overfitting, and sensitivity to environmental noise.

3. PROPOSE SYSTEM

Fig. 2 shows the system architecture begins with cotton leaf image acquisition from the dataset, where images are organized into folders corresponding to output classes. The input images pass through an image preprocessing module to standardize quality and format. After preprocessing, the dataset is split into training and testing subsets. Multiple models, including existing Bagging, LGBM, and CNN-RF classifiers, are built for performance comparison. The proposed ResNet50 with LDA model extracts deep discriminative features and classifies them into disease categories. The final stage produces disease prediction outputs and performance metrics for evaluation.

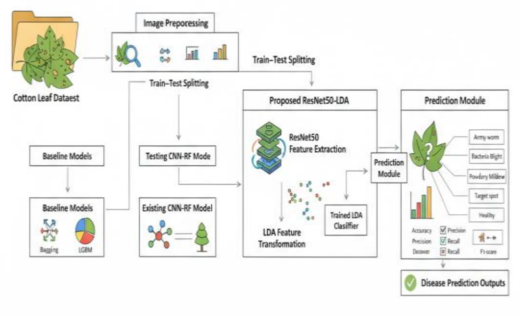

Fig. 2: Proposed system architecture.

Cotton Images: Cotton leaf images are collected from the dataset, where each disease category is organized into separate folders representing the output classes. These images serve as the raw input to the system and include both healthy and early-stage diseased leaf samples captured under varying conditions.

Image Preprocessing: Each input image passes through the preprocessing block, where resizing, normalization are applied. This step standardizes image dimensions and pixel intensity distributions, enabling uniform feature learning across the dataset.

Train–Test Splitting: The labeled dataset is divided into training and testing subsets using a fixed ratio. Class-wise distribution is maintained in both subsets to prevent bias and ensure reliable performance evaluation.

Baseline Model Construction: Existing machine learning models, including the Bagging classifier and LGBM classifier, are trained using the training dataset. These models rely on extracted features and serve as reference systems for comparative analysis.

Existing CNN-RF Model: A convolutional neural network extracts deep visual features from the training images. These features are then passed to a Random Forest classifier, which performs ensemble-based decision making for disease classification.

Proposed ResNet50-LDA: The preprocessed training images are forwarded through the pretrained ResNet50 network. The network's convolutional and residual layers generate high-dimensional deep feature vectors that capture both local and global disease characteristics. The extracted ResNet50 features are transformed using Linear Discriminant Analysis. This step reduces feature dimensionality while maximizing class separability, making early-stage disease patterns more distinguishable.

Prediction From Test Image: The sample unknown images are considered for prediction. The ResNet50 optimized LDA features are classified into their respective disease categories such as Aphids, Army worm, Bacteria Blight, Powdery Mildew, Target spot and Healthy using the trained LDA classifier. Each test image is assigned an output class corresponding to its folder name. The system generates the final disease diagnosis results along with performance statistics. These outputs provide clear identification of cotton leaf health status and support early-stage disease management decisions.

Performance Evaluation: The predicted outputs are compared with ground-truth labels from the test dataset. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to assess system effectiveness.

3.1 sResNet50 Feature Extraction with LDA Classifier

Fig 3 shows proposed model integrates deep residual learning with statistical feature discrimination to enhance early-stage disease diagnosis. ResNet50 is employed solely as a feature extractor, reducing training overhead while preserving rich spatial information. The extracted features are refined using LDA to improve class separability. This approach balances accuracy and efficiency, making it suitable for practical agricultural applications.

Input to Deep Feature Extractor: Preprocessed cotton leaf images from the training set are fed into a pretrained ResNet50 network. The network acts purely as a feature extractor without retraining all layers.

Deep Feature Generation: ResNet50 generates rich feature vectors capturing texture, color variation, and lesion structure associated with early-stage cotton diseases.

Feature Refinement and Classification: The extracted features are refined and classified using Linear Discriminant Analysis, which enhances class separability and reduces dimensionality. The final output is the predicted disease class corresponding to the dataset folder names, forming the proposed diagnostic result.

Training Phase Optimization: The LDA classifier is trained using the refined feature vectors obtained from ResNet50. During this phase, class-wise statistical parameters such as mean vectors and scatter matrices are computed to establish optimal decision boundaries.

Validation and Performance Evaluation: The trained model is evaluated on validation and test datasets using performance metrics including accuracy, precision, recall, F1-score, and confusion matrix to assess classification effectiveness across all disease categories.

Disease Class Decision Mapping: Based on the LDA decision function, each test image is assigned to the disease class with the highest discriminant score, ensuring reliable differentiation between visually similar early-stage disease symptoms.

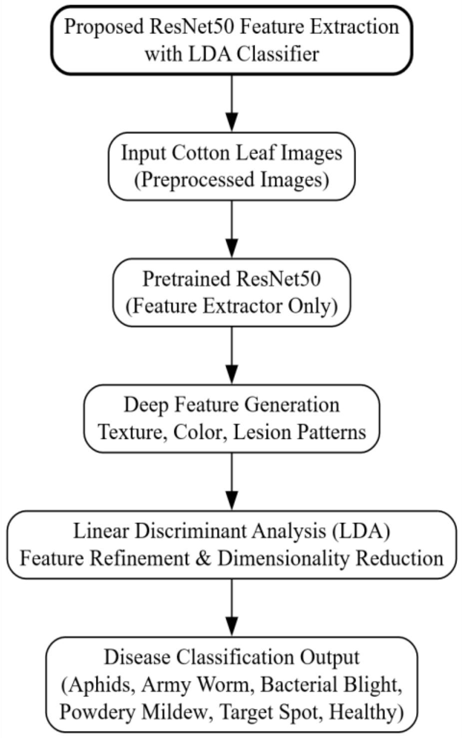

Fig. 3: Proposed ResNet50 feature extraction with LDA model flowchart

Output Visualization and Reporting: The predicted disease class is displayed along with corresponding labels, enabling easy interpretation for agricultural experts and facilitating timely disease management decisions.

Deployment for Practical Application: The lightweight architecture of the ResNet50–LDA model allows deployment on resource-constrained agricultural systems, supporting real-time cotton disease diagnosis in field conditions.

4. Results Analysis

Fig. 4 illustrates the confusion matrix of the existing bagging model, where noticeable misclassifications are observed across multiple attack categories, particularly between Grayhole and Blackhole classes, indicating limited discriminative capability and reduced reliability in multi-class attack scenarios. Fig. 5 presents the confusion matrix of the CNN-RF model, which shows improved classification performance compared to bagging yet still exhibits misclassification among closely related attack types, especially TDMA and Grayhole, reflecting moderate learning effectiveness. Fig. 6 depicts the confusion matrix of the LGBM model, where classification accuracy further improves with reduced error rates; however, some confusion persists among minority attack classes, indicating incomplete separation of complex attack patterns.

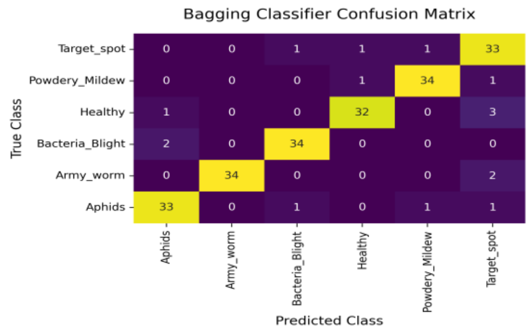

Fig. 4: Confusion matrix of existing bagging model.

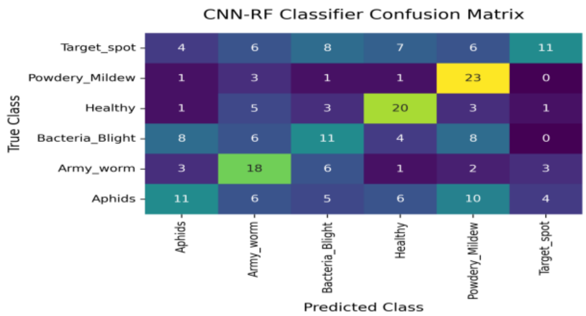

Fig. 5: Confusion matrix of existing CNN-RF model.

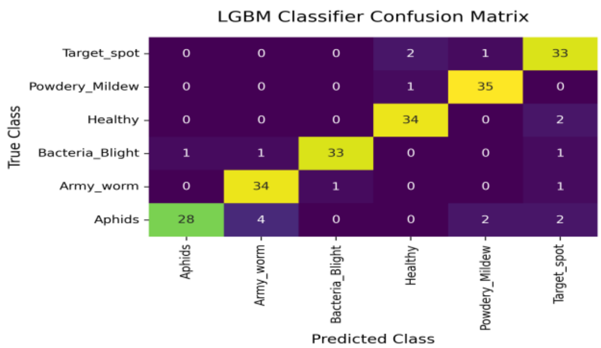

Fig. 6: Confusion matrix of existing LGBM model.

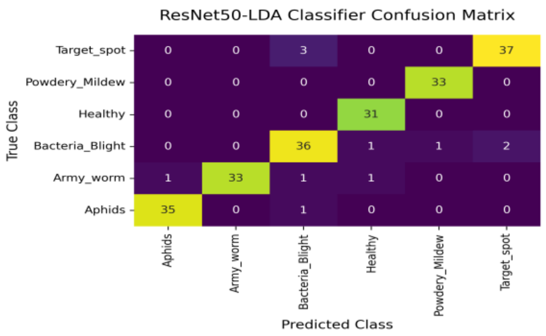

Fig. 7: Confusion matrix of proposed ResNet50-LDA model.

(a)

(b)

(c)

Fig. 8: Predictions result on test images. (a) Aphids, (b) Army_worm, (c) Bacteria_Blight.

Fig. 8 (a) demonstrates the practical application of the ResNet50-LDA classifier in diagnosing specific cotton leaf pests. By utilizing deep visual features extracted via the pretrained ResNet50 and refined through Linear Discriminant Analysis, the system successfully

Fig. 7 shows the confusion matrix of the proposed ResNet50-LDA model, which demonstrates highly concentrated diagonal values with negligible off-diagonal entries, confirming precise classification of Normal, Flooding, TDMA, Grayhole, and Blackhole attacks. The proposed model achieves superior class separability and minimizes misclassification across all categories, validating its effectiveness and robustness for accurate WSN attack detection in comparison with existing approaches.

identifies the unique morphological characteristics of Aphids with high confidence. This specific diagnostic output is a key component of the "Prediction from Test Image" stage, where unknown leaf samples are processed to generate both a visual diagnosis and supporting performance statistics. The high reliability of these results is further supported by the class-wise performance metrics, which show the model achieving a Recall of 0.97 and a Precision of 0.97 for the Aphids class.

Fig. 8 (b) demonstrates the robust classification capability of the Proposed ResNet50-LDA Classifier in a real-world diagnostic scenario. In this instance, the system correctly identifies the presence of an armyworm and its characteristic feeding damage on the cotton leaf, which aligns with the high classification performance seen in the model's architectural evaluation. This visual confirmation is backed by the quantitative data from the ResNet50-LDA Classifier Confusion Matrix, which shows that 33 instances of Army_worm were correctly identified, maintaining a strong precision of 1.0 for this specific class. By successfully processing deep visual features through the ResNet50-LDA pipeline, the model provides an accurate "Prediction from Test Image" result, effectively distinguishing the pest from other conditions like Bacteria Blight or Target spot.

Fig. 8 (c) showcases the model's high proficiency in identifying the angular, water-soaked lesions and necrotic spots characteristic of this bacterial infection. This successful diagnosis is a direct outcome of the ResNet50-LDA architecture, which utilizes deep feature extraction and Linear Discriminant Analysis to achieve high class separability. The accuracy of this specific prediction is reflected in the model's performance metrics, where Bacteria_Blight achieved 36 correct classifications out of the test set, maintaining a robust Recall of 0.9 and a Precision of 0.88. By providing this visual classification alongside performance statistics, the system completes the final stage of the proposed system architecture: generating a reliable diagnosis from an unknown test image.

Table 1: Performance comparison of classification quality metrics.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Bagging Model	92.59	92.86	92.59	92.66
LGBM Model	91.2	91.57	91.2	91.14
CNN-RF Model	43.52	44.33	46.1	42.93
ResNet50-LDA Model	94.91	95.15	95.23	95.14

Table 1 comparative performance analysis of the various models, as detailed in the provided data, highlights the significant improvement achieved by the Proposed ResNet50-LDA architecture over existing methodologies. According to the performance statistics, the ResNet50-LDA model outperforms all other classifiers, reaching the highest Accuracy of 94.91%, Precision of 95.15%, Recall of 95.23%, and an F1-Score of 95.14%. In comparison, the baseline Bagging and LGBM models show strong but lower results, with accuracies of 92.59% and 91.2% respectively. The CNN-RF model, which serves as an existing deep learning reference, demonstrates the lowest performance across all metrics, with an Accuracy of only 43.52% and an F1-Score of 42.93%, likely due to less effective feature integration compared to the LDA-enhanced approach. These values, which would be represented in a performance summary table like Figure 6.2, confirm that using a pretrained ResNet50 for deep visual feature extraction combined with LDA for dimensionality reduction significantly optimizes the classification of cotton leaf diseases.

5. Conclusion

The implementation of the ResNet50-LDA architecture has established a new benchmark for cotton leaf disease analysis, significantly outperforming existing baseline models across all critical evaluation metrics. By leveraging a pretrained ResNet50 for deep feature extraction and Linear Discriminant Analysis for enhanced class separability, the proposed system achieved a peak Accuracy of 94.91% and a Macro F1-Score of 0.95. These results represent a substantial improvement over the LGBM baseline's accuracy of 91.2% and a massive leap from the CNN-RF model's 43.52% accuracy. The model's robustness is further evidenced by its perfect Recall of 1.0 for both Healthy and Powdery_Mildew classes, effectively eliminating false negatives in these categories. This level of precision and reliability ensures that the system can be trusted for real-time agricultural monitoring, where accurate diagnosis is vital for crop preservation.

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