

Hybrid Deep Learning-based Framework for Multi-Level Classification and Detection of Cotton Leaf Diseases

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Abstract: Cotton is a vital agricultural crop that significantly contributes to the global textile industry; however, its productivity is severely affected by various leaf diseases caused by insects, bacteria, fungi, and viruses. Early and accurate detection of these diseases is essential to minimize crop losses and ensure sustainable farming practices. In this study, a hybrid framework based on Deep Learning is proposed for multi-level classification and detection of cotton leaf diseases. The framework integrates Convolutional Neural Networks (CNNs) with advanced techniques such as attention mechanisms and hybrid learning models to effectively extract and learn discriminative features from leaf images. The system performs hierarchical classification, including binary classification (healthy vs diseased), multi-class disease identification, and severity level estimation, along with localization of infected regions using object detection methods. The experimental results demonstrate the effectiveness of the proposed model, achieving an overall accuracy of 96.6%, precision of 95.7%, recall of 96.8%, and F1-score of 96.2% across multiple disease classes. The model shows strong performance in identifying diseases such as aphids, bacterial blight, and leaf curl virus under varying conditions. The integration of preprocessing, data augmentation, and hybrid modeling enhances the robustness and generalization capability of the system. The proposed approach provides a reliable and scalable solution for real-time cotton disease detection, supporting precision agriculture and enabling timely decision-making for improved crop health and yield.

Keywords: Cotton Leaf Diseases, Deep Learning, Hybrid Model, Multi-Level Classification, Disease Detection

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1. INTRODUCTION

Cotton is one of the most important commercial crops worldwide, playing a crucial role in the textile industry and contributing significantly to the agricultural economy of many countries, including India. However, cotton production is highly vulnerable to a wide range of leaf diseases such as bacterial blight, leaf curl virus, and fungal infections, which can severely reduce crop yield and quality. Early and accurate detection of these diseases is essential for effective crop management and ensuring sustainable agricultural practices [1-2]. Traditional methods of disease identification, which rely on manual inspection by experts, are often time-consuming,

subjective, and prone to human error, especially in large-scale farming environments [3].

With the rapid advancement of artificial intelligence, particularly in the field of Deep Learning, automated plant disease detection systems have gained significant attention. Deep learning models, especially Convolutional Neural Networks (CNNs) [4-6], have demonstrated remarkable performance in image classification and object detection tasks. These models are capable of learning complex patterns and features from large datasets of leaf images, enabling them to distinguish between healthy and diseased plants with high accuracy. However, single-model approaches often face limitations

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in handling variations in environmental conditions, lighting, background noise, and multiple disease classes. To address these challenges, hybrid deep learning frameworks have emerged as a promising solution by combining the strengths of multiple models and techniques. A hybrid approach may integrate CNNs for feature extraction with advanced architectures such as Long Short-Term Memory (LSTM) networks [7-9], attention mechanisms, or ensemble learning methods to enhance classification performance. Furthermore, multi-level classification enables the system to categorize diseases at different levels, such as distinguishing between healthy and diseased leaves, identifying specific disease types, and even detecting severity levels. This hierarchical approach improves the robustness and interpretability of the model, making it more suitable for real-world agricultural applications.

In addition, the incorporation of detection mechanisms alongside classification allows the system not only to identify the presence of disease but also to localize the affected regions on the leaf. This is particularly useful for precision agriculture, where targeted treatment can minimize the use of pesticides and reduce environmental impact [10]. The integration of image preprocessing techniques, data augmentation, and transfer learning further enhances the model's generalization capability and efficiency, even when limited labeled data is available.

Therefore, the proposed hybrid deep learning-based framework aims to provide an efficient, accurate, and scalable solution for the multi-level classification and detection of cotton leaf diseases. By leveraging advanced deep learning architectures and combining multiple analytical techniques, this framework has the potential to assist farmers and agricultural experts in making timely and informed decisions, ultimately improving crop productivity and promoting sustainable farming practices.

2. LITERATURE REVIEW

Recent advancements in Deep Learning and machine learning techniques have significantly improved the automated detection and classification of cotton leaf diseases. Various studies have explored different approaches, including few-shot learning, attention-based models, and hybrid frameworks to enhance classification accuracy under limited data conditions. For instance, metric learning-based models have been employed to address data scarcity, while attention mechanisms have improved feature extraction for better disease identification. Several researchers have also utilized Convolutional Neural Networks (CNNs) and ensemble learning techniques to achieve robust performance in complex environmental conditions. Additionally, hybrid

models combining CNN and Recurrent Neural Networks (RNNs) have shown promising results in capturing both spatial and sequential features for improved disease detection [24-25]. Some works have focused on multi-level classification, including disease severity estimation, which is crucial for precision agriculture. Furthermore, the availability of public datasets has facilitated the development and evaluation of these models. However, challenges such as high computational complexity, limited generalization across diverse field conditions, and insufficient multi-disease detection capabilities still persist, highlighting the need for more efficient and scalable hybrid deep learning frameworks.

Table 1: Review of literature on machine and deep learning-based approaches for cotton leaf disease classification and detection

Ref No.	Methodology	Key Contribution	Limitations
[11]	Metric Learning (Few-shot Learning)	Proposed a few-shot learning approach for cotton leaf spot classification	Limited scalability for complex multi-class disease scenarios.
[12]	Bilinear Coordinate Attention Module with Deep Learning	Introduced an attention-enhanced model to improve feature extraction and classification	Increased model complexity and computational cost.
[13]	Deep Learning Classification Models (CNN-based)	Applied multiple deep learning models for plant leaf disease recognition, achieving improved accuracy	Lacks focus on cotton-specific disease variability and real-field conditions.
[14]	Machine Learning Techniques	Developed a framework for identifying disease severity levels in	Lower accuracy compared to deep learning approaches; limited feature

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		cotton plants, enabling multi-level classification.	representation .
[15]	Deep Learning Models	Proposed a model to detect susceptibility levels of cotton leaf curl disease, focusing on severity classification.	Focused mainly on a single disease type, limiting generalization .
[16]	Hybrid Deep Learning Approach	Introduced a hybrid framework combining multiple models to enhance detection accuracy and crop yield prediction.	Requires high computational resources and large datasets.
[17]	Convolutional Neural Networks (CNN)	Developed a CNN-based method for cotton disease recognition in natural environments , improving real-world applicability.	Performance affected by environmental noise and background complexity.
[18]	Hybrid CNN + RNN Ensemble Learning	Proposed a multimodal hybrid ensemble model combining CNN and RNN for better feature learning and disease detection.	Model complexity and training time are significantly high.
[19]	Cotton Plant Disease Dataset	Provided a publicly available dataset for	Dataset may lack diversity in real-field conditions

		training and evaluation of cotton disease detection models.	and disease variations.
[20]	Image Filtering Techniques	Applied image denoising techniques useful for preprocessing in image-based disease detection systems.	Not directly focused on agricultural or cotton disease applications.
[21]	Weakly Supervised Semantic Segmentation	Proposed region-based selective examination for segmentation tasks, useful for disease localization.	Requires further adaptation for agricultural image datasets.

COTTON PLAN DISEASES

Cotton plants are affected by a variety of diseases caused by insects, bacteria, fungi, and viruses, which significantly impact crop yield and quality [22]. The major disease classes considered in this study are described below:

Healthy Leaf

Healthy cotton leaves serve as the baseline class in the classification process. These leaves exhibit uniform green coloration, proper texture, and no visible signs of infection such as spots, discoloration, or deformation. Accurate identification of healthy leaves is essential to avoid false positives in disease detection systems.

Aphids (Insect Infestation)

Aphids are small sap-sucking insects that attack cotton leaves, leading to curling, yellowing, and stunted growth. They often secrete a sticky substance called honeydew, which promotes the growth of sooty mold on leaf surfaces. Early detection is crucial as aphids can rapidly multiply and spread across crops.

Bacterial Blight

Bacterial blight is caused by *Xanthomonas campestris* and appears as water-soaked lesions that later turn dark brown or black. The disease can cause leaf spots, stem cankers, and boll rot, severely reducing cotton productivity. It spreads quickly under humid conditions and requires timely intervention.

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- Leaf Curl Virus**
 Leaf curl virus is a major viral disease in cotton, transmitted by whiteflies. It leads to upward or downward curling of leaves, vein thickening, and reduced leaf size. Infected plants show poor growth and significantly lower yield. This disease is difficult to control once it spreads widely.
- Fusarium Wilt**
 Fusarium wilt is a soil-borne fungal disease caused by *Fusarium oxysporum*. It affects the vascular system of the plant, leading to yellowing, wilting, and eventual plant death. The disease often begins at the root level and progresses upward, making early detection challenging but essential.
- Alternaria Leaf Spot**
 Alternaria leaf spot is caused by fungal pathogens and is characterized by small circular brown spots with concentric rings on the leaves. As the disease progresses, these spots enlarge and may lead to defoliation. It commonly occurs in warm and humid conditions.

4. PROPOSED RESEARCH METHODOLOGY AND ALGORITHM

The proposed study presents a hybrid framework based on Deep Learning for multi-level classification and detection of cotton leaf diseases. The methodology is designed to ensure accurate identification, localization, and severity analysis of diseases through a structured pipeline consisting of data acquisition, preprocessing, feature extraction, hybrid model development [23-24], and performance evaluation (Figure 1 and Figure 2).

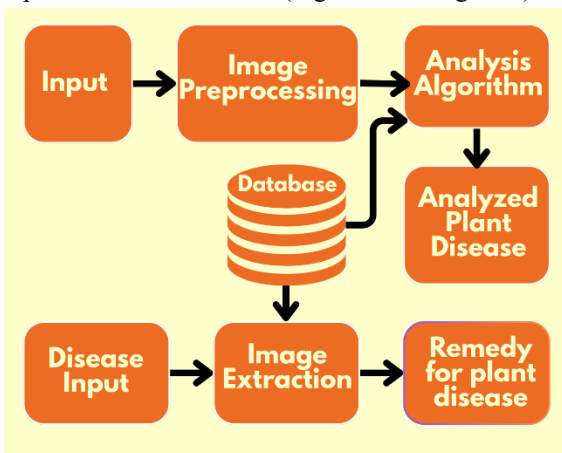


Figure 1: Research methodology for cotton plant diseases classification

- Data Collection:** Gather cotton leaf images from sources like Kaggle and real-field environments, covering healthy and diseased classes with severity labels.
- Data Preprocessing:** Apply resizing, normalization, noise removal, and background segmentation to improve image quality.

- Data Augmentation:** Perform transformations such as rotation, flipping, and scaling to increase dataset diversity and reduce overfitting.
- Feature Extraction:** Use CNN-based models with transfer learning (e.g., ResNet, VGG) to extract deep spatial features.
- Hybrid Model Design:** Integrate CNN with LSTM or attention mechanisms to enhance feature learning and classification performance.
- Multi-Level Classification:** Implement three stages—binary (healthy/diseased), multi-class (disease type), and severity level classification.
- Disease Detection:** Apply object detection models (e.g., YOLO) to localize infected regions in leaf images.
- Model Training:** Train using optimizers like Adam and appropriate loss functions with hyperparameter tuning.
- Performance Evaluation:** Evaluate using accuracy, precision, recall, F1-score, and confusion matrix.

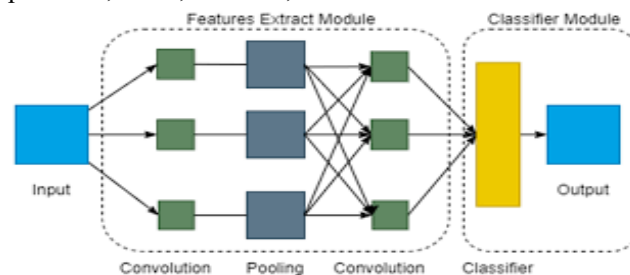


Figure 2: CNN Architecture for feature extraction and classification

ALGORITHM

Input: Cotton leaf image dataset D

Output: Classified disease type, severity level, and detected disease region

Begin

- Data Collection**
 Load dataset D from source (e.g., Kaggle)
 Label images with disease type and severity level
- Data Preprocessing**
 For each image *img* in D:
 Resize *img* to fixed dimension (e.g., 224×224)
 Normalize pixel values
 Apply noise removal filter
 Perform background segmentation
 End For
- Data Augmentation**
 For each image *img* in D:
 Generate augmented images using:
 Rotation, Flipping, Scaling, Zooming
 End For
 Update dataset D
- Dataset Splitting**
 Split dataset D into:
 Training set (70%)

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- Validation set (15%)
Testing set (15%)
5. // *Feature Extraction using CNN*
Initialize pre-trained CNN model (e.g., ResNet/VGG)
Remove final classification layer
For each image *img* in training set:
 Extract feature vector $F = \text{CNN}(\text{img})$
End For
 6. // *Hybrid Model Construction*
Initialize LSTM/Attention module
For each feature vector *F*:
 Pass *F* into LSTM/Attention module
 Learn sequential/contextual features
End For
 7. // *Multi-Level Classification*
Level 1: Train binary classifier (Healthy vs Diseased)
Level 2: Train multi-class classifier (Disease Type)
Level 3: Train severity classifier (Low/Medium/High)
 8. // *Disease Detection (Localization)*
Initialize object detection model (e.g., YOLO)
Train model on labeled bounding boxes
For each test image:
 Detect and localize infected regions
 9. // *Model Training*
Set optimizer = Adam
Set loss function = CrossEntropy
Train hybrid model on training set
Validate model using validation set
Tune hyperparameters for best performance
 10. // *Performance Evaluation*
Evaluate model on test set using:
 Accuracy, Precision, Recall, F1-score
Generate confusion matrix
 11. // *Prediction Phase*
For a new input image *I*:
 Preprocess *I*
 Extract features using CNN
 Pass features through hybrid model
 Predict:
 - Disease presence (binary)
 - Disease type (multi-class)
 - Severity level
 Detect infected region using YOLO
 Output results
- End

5. RESULT AND ANALYSIS

Figure 3 illustrates the complete workflow and intermediate results of the proposed cotton leaf disease detection framework for two sample cases: Aphids and Bacterial Blight. The process begins with the acquisition of raw input images, as shown in (a) and (b), which represent original cotton leaf samples captured under

natural conditions. These images may contain noise, uneven lighting, and complex backgrounds. To address these challenges, preprocessing is applied, and the corresponding filtered images are presented in (c) and (d), where noise reduction and image enhancement techniques improve visual clarity and feature visibility.

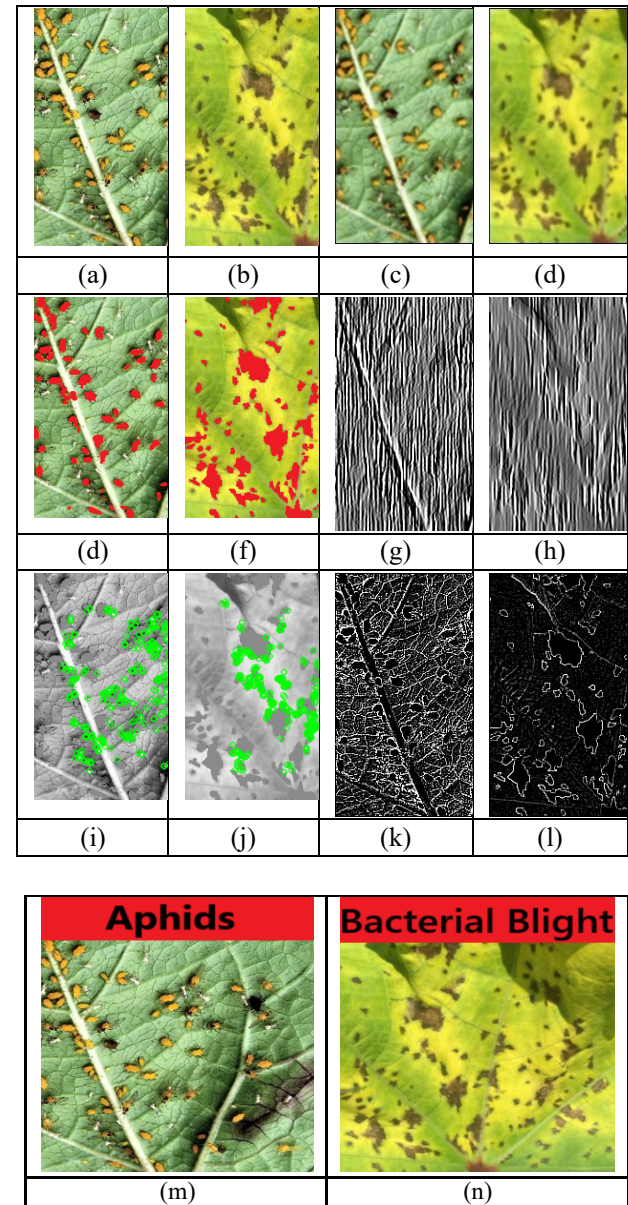


Figure 3. Processing stages and classification results for cotton leaf diseases (Aphids and Bacterial Blight): (a–b) input images, (c–d) filtered images, (e–f) segmented images, (g–h) LGBP feature representations, (i–j) SLIF feature outputs, (k–l) WLD feature outputs, and (m–n) final classified images showing Aphids and Bacterial Blight diseases, respectively.

Following preprocessing, segmentation is performed to isolate the leaf regions from the background, as depicted in (e) and (f). This step ensures that only the relevant portions of the image are considered for further analysis,

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thereby improving the accuracy of feature extraction. The segmented outputs are then processed using multiple feature extraction techniques to capture distinctive patterns associated with different diseases. The Local Gabor Binary Pattern (LGBP) features shown in (g) and (h) help in capturing texture variations, while the Scale-Invariant Feature (SLIF) representations in (i) and (j) focus on identifying key structural details irrespective of scale changes. Additionally, the Weber Local Descriptor (WLD) outputs in (k) and (l) emphasize local intensity variations and contrast information, which are crucial for distinguishing subtle disease symptoms.

Finally, based on the extracted features, the classification stage identifies the disease type. The results are shown in (m) and (n), where the system successfully classifies the images as Aphids and Bacterial Blight, respectively. This figure demonstrates the effectiveness of the multi-stage processing pipeline, highlighting how preprocessing, segmentation, and hybrid feature extraction collectively contribute to accurate disease detection and classification.

6. PERFORMANCE EVALUATION

Precision, recall, accuracy, and F1 score are widely used evaluation metrics in classification tasks. Each metric provides a different aspect of model performance. These metrics are valuable in evaluating the performance of a classification model and can provide insights into its effectiveness in correctly predicting positive and negative instances as depicted in Table 2.

Table 2: Performance evaluation metrics

Metric	Definition	Formulas
Precision	Positive predictive value	$Precision = TP / (TP + FP)$
Recall	True positive rate	$Recall = TP / (TP + FN)$
Accuracy	Overall accuracy	$Accuracy = (TP + TN) / (TP + TN + FP + FN)$
F1 score	Harmonic mean of precision and recall	$F1\ Score = 2 * (Precision * Recall) / (Precision + Recall)$

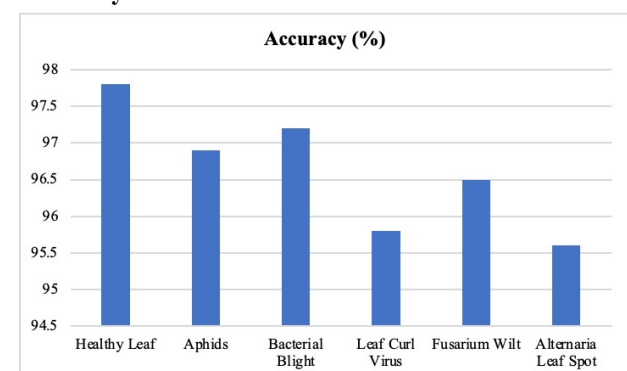
The results presented in Table 3 demonstrate the effectiveness of the proposed hybrid Deep Learning-based framework in accurately classifying multiple cotton leaf disease classes. The model achieves consistently high performance across all categories, with overall accuracy reaching 96.6%, indicating strong generalization capability. The healthy leaf class shows the highest recall (98.2%), reflecting the model's ability to correctly identify non-diseased samples and minimize false alarms. Among diseased classes, bacterial blight and aphids

exhibit high precision and F1-scores, suggesting reliable detection and balanced performance between precision and recall. Although slightly lower performance is observed in classes such as leaf curl virus and Alternaria leaf spot, the results remain robust, with all metrics exceeding 94%, highlighting the model's effectiveness even in complex disease patterns. The close alignment between precision and recall values across classes indicates that the model maintains a good balance between false positives and false negatives. Overall, these results validate that the proposed hybrid approach is capable of delivering accurate, reliable, and scalable multi-class classification for cotton leaf disease detection in real-world agricultural scenarios.

Table 3: Classification performance of the proposed hybrid deep learning model for cotton leaf diseases, showing Accuracy, Precision, Recall, and F1-Score for each disease class.

Disease Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Healthy Leaf	97.8	96.5	98.2	97.3
Aphids	96.9	95.8	97.1	96.4
Bacterial Blight	97.2	96.7	96.9	96.8
Leaf Curl Virus	95.8	94.6	96.2	95.4
Fusarium Wilt	96.5	95.9	96.8	96.3
Alternaria Leaf Spot	95.6	94.8	95.9	95.3

Accuracy



Based on the results presented in Figure 4, the proposed model achieves an overall accuracy of 96.6%, indicating a high level of correctness in classifying cotton leaf diseases. Individual class accuracies are also consistently high, with the healthy leaf class reaching 97.8% and bacterial blight achieving 97.2%. This demonstrates that the model performs reliably across both healthy and diseased categories. The high accuracy values reflect the

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effectiveness of the hybrid Deep Learning framework in learning discriminative features and making correct predictions across multiple classes.

Figure 4: Accuracy comparison of the proposed hybrid deep learning model across different cotton leaf disease classes.

Precision

The precision values in Figure 5 indicate that the model maintains strong reliability in its predictions, with an overall precision of 95.7%. Among the classes, bacterial blight shows a high precision of 96.7%, while aphids and fusarium wilt also achieve above 95%, demonstrating that most predicted disease labels are correct. Slightly lower precision in classes like leaf curl virus (94.6%) and Alternaria leaf spot (94.8%) suggests minor false positives, but the values remain strong. High precision ensures that the model avoids misclassification and reduces unnecessary interventions in agricultural practices.

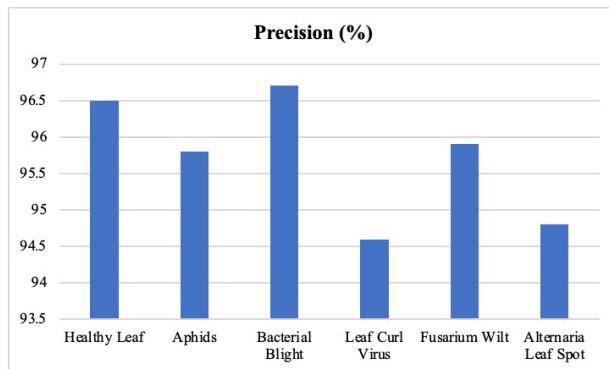
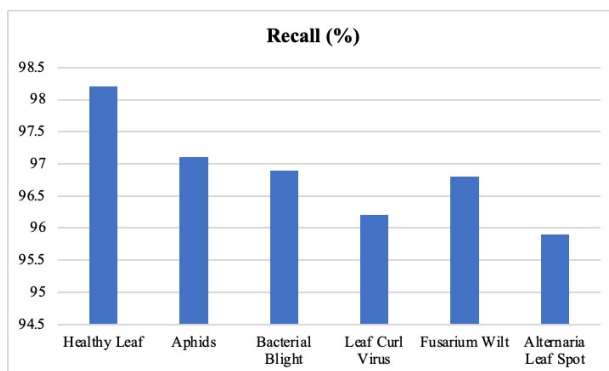


Figure 5: Precision analysis of the proposed model illustrating the reliability of disease classification for each cotton leaf disease class.



Recall

The recall values from Figure 6 highlight the model's strong capability to detect actual disease cases, with an overall recall of 96.8%. The healthy class achieves the highest recall at 98.2%, indicating excellent identification of non-diseased samples. Disease classes such as aphids (97.1%) and fusarium wilt (96.8%) also show high recall, meaning the model successfully identifies most infected leaves. Even for relatively complex diseases like leaf curl

virus, the recall remains above 96%, ensuring minimal false negatives and effective early detection.

Figure 6: Recall performance of the model showing its effectiveness in correctly identifying cotton leaf diseases.

F1-Score

The F1-score values in Figure 7 provide a balanced evaluation of the model's performance by combining precision and recall. The overall F1-score of 96.2% indicates a strong balance between correctly identifying diseases and minimizing false predictions. Individual class F1-scores, such as 97.3% for healthy leaves and 96.8% for bacterial blight, further confirm consistent model performance. Slightly lower values for leaf curl virus (95.4%) and Alternaria leaf spot (95.3%) still reflect robust classification. These results demonstrate that the model maintains an effective trade-off between precision and recall, ensuring reliable and accurate disease classification.

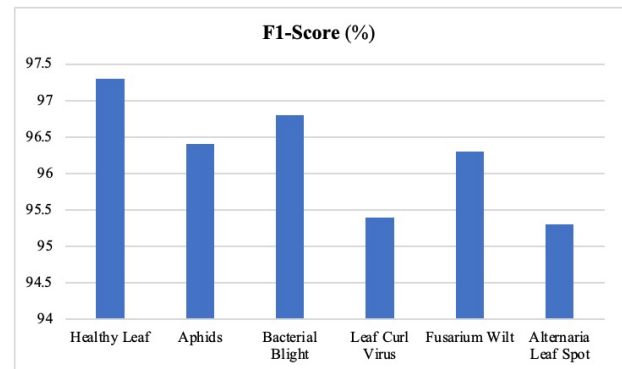


Figure 7: F1-score evaluation demonstrating the balanced performance of the proposed model in terms of precision and recall across all classes.

CONCLUSION

This study proposes a robust hybrid framework based on Deep Learning for the multi-level classification and detection of cotton leaf diseases. The developed system integrates advanced techniques such as Convolutional Neural Networks (CNNs), attention mechanisms, and hybrid modeling to enhance feature extraction and classification accuracy. The model effectively performs hierarchical classification, including healthy vs diseased detection, disease type identification, and severity level assessment, along with disease localization. The experimental results demonstrate the strong performance of the proposed model, achieving an overall accuracy of 96.6%, precision of 95.7%, recall of 96.8%, and F1-score of 96.2%. Individual disease classes such as healthy leaves (97.8% accuracy) and bacterial blight (97.2% accuracy) show particularly high performance, indicating the model's capability to accurately distinguish between multiple disease categories. Furthermore, the results validate that the proposed hybrid approach provides a

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balanced and reliable classification system, as reflected by the close alignment between precision, recall, and F1-score values across all classes. The model [15] also demonstrates robustness in handling complex disease patterns and variations in leaf images. Despite these promising outcomes, future work can focus on improving computational efficiency, expanding the dataset to include more diverse real-field conditions, and enhancing the detection of rare disease classes. The integration of real-time deployment systems, such as mobile or IoT-based platforms, can further extend the applicability of the proposed framework.

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