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A Hybrid CNN–Transformer–LSTM Deep Learning Framework for Automated Cotton Disease Detection

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ABSTRACT: Cotton production is frequently affected by leaf diseases that can reduce plant productivity, deteriorate crop quality, and cause considerable financial losses for farmers. Consequently, rapid and reliable disease identification is an important requirement for precision agriculture and effective crop protection. Conventional image-based approaches predominantly employ CNN architectures for visual classification; however, such methods may have limited capability in learning long-range spatial dependencies and modeling changes associated with disease development over time. To overcome these limitations, this research introduces an integrated hybrid deep learning framework that combines Convolutional Neural Networks (CNNs), Transformer-based self-attention, and Long Short-Term Memory (LSTM) networks for intelligent cotton leaf disease recognition. The proposed framework utilizes a pre-trained EfficientNet network to extract discriminative spatial characteristics from cotton leaf images. The extracted representations are subsequently processed through a multi-head self-attention Transformer module, which enables the network to identify relationships between distant and relevant regions of the leaf. An LSTM component is then incorporated to learn sequential dependencies and provide a foundation for analyzing disease evolution and progression. To improve model reliability and generalization, the network is trained using an appropriately organized cotton leaf image dataset together with image augmentation, transfer learning, and fine-tuning techniques. The experimental evaluation indicates that the proposed CNN–Transformer–LSTM architecture provides improved disease classification performance and more effective feature learning compared with conventional CNN-based models. Performance assessment using classification metrics, confusion matrices, and ROC curves demonstrates strong discrimination among the considered cotton disease categories. The combined learning of local visual characteristics, global contextual information, and sequential dependencies provides a comprehensive framework for automated cotton disease assessment. The proposed approach can serve as a scalable artificial intelligence solution for precision agriculture applications. Its architecture also provides opportunities for future integration with IoT-based crop monitoring systems, environmental data acquisition, and disease progression prediction, supporting early warning systems and intelligent crop health management in smart farming environments.

1. INTRODUCTION

Cotton is among the world's major commercial fiber crops and contributes substantially to agricultural economies, textile industries, and rural livelihoods. Despite its economic importance, cotton cultivation is continuously threatened by several diseases that primarily affect the leaves and other plant tissues. Diseases such as Alternaria leaf spot, bacterial blight, anthracnose, and leaf curl virus can adversely influence plant growth, reduce photosynthetic activity, and ultimately cause considerable losses in both crop productivity and quality. Consequently, timely identification of disease symptoms is essential for implementing appropriate treatment strategies and minimizing agricultural losses. Conventional disease diagnosis generally depends on visual examination performed by farmers or agricultural specialists. Although expert inspection can provide useful diagnostic information, it is labor-intensive, subjective, and difficult to apply consistently across extensive agricultural fields.

The development of artificial intelligence and computer vision has created new opportunities for automating plant disease identification. In particular, deep learning methods have demonstrated considerable potential for analyzing plant images and recognizing disease-specific visual characteristics. Convolutional Neural Networks (CNNs) have become widely adopted for this purpose because of their ability to automatically learn hierarchical representations from image data. CNN architectures can identify important characteristics such as leaf texture, color variation, lesion structures, and disease-specific patterns without requiring extensive manual feature engineering. Several established architectures, including VGG, ResNet, EfficientNet, and YOLO-based approaches, have achieved promising results in plant disease classification and detection. Nevertheless, conventional CNN-based systems generally concentrate on local spatial information within individual images and may not adequately represent long-range relationships between different regions of a diseased leaf. Moreover, many existing systems are designed for independent image classification rather than continuous monitoring of disease development.

Transformer architectures have recently become an important alternative for visual feature learning because of their self-attention mechanism. The attention mechanism enables a model to establish relationships between distant image regions and therefore provides a broader representation of the visual scene. This characteristic is particularly relevant to plant disease analysis because symptoms may occur at multiple locations on a leaf and can exhibit irregular spatial distributions. While CNNs are effective at extracting localized patterns, Transformer models can complement this capability by learning global contextual dependencies. Despite the increaasing application of Vision Transformers and attention-based architectures in computer vision, their use specifically for cotton leaf disease recognition remains comparatively limited. Furthermore, the combined utilization of CNN-based spatial feature extraction and Transformer-based global representation has not been sufficiently explored for comprehensive cotton disease analysis.

Another important limitation of many existing plant disease recognition systems is their dependence on isolated images. Disease development is inherently dynamic, and visible symptoms may change progressively according to environmental and biological conditions. Factors such as temperature, humidity, soil properties, irrigation conditions, and pathogen activity can influence the development and severity of plant diseases. Consequently, analyzing a sequence of observations rather than a single image may provide additional information regarding disease progression. Long Short-Term Memory (LSTM) networks are specifically designed to learn dependencies within sequential data and can retain relevant information over multiple time steps. Incorporating LSTM-based temporal learning into an image-based disease detection framework can therefore provide a pathway toward monitoring changes in disease symptoms and supporting future progression prediction.

Considering these limitations, this study proposes an integrated hybrid deep learning architecture based on CNN, Transformer, and LSTM networks for intelligent cotton leaf disease analysis. The proposed framework employs a pre-trained EfficientNet model as the primary feature extraction backbone for learning representative spatial characteristics from cotton leaf images. The extracted feature representations are subsequently processed by a multi-head self-attention Transformer module to capture global relationships among different leaf regions. An LSTM network is then incorporated to model sequential feature dependencies, thereby establishing a foundation for temporal disease progression assessment. By combining local spatial representation, global contextual attention, and temporal sequence learning, the proposed architecture aims to provide a more comprehensive representation of cotton disease characteristics than conventional single-model approaches.

The proposed framework is intended not only to improve the reliability of cotton disease classification but also to establish a scalable architecture for future intelligent agricultural applications. The integration of spatial, contextual, and temporal learning can potentially support continuous crop health assessment, early disease warning, and predictive agricultural decision-making. In addition, the framework can subsequently be connected with IoT-based monitoring systems in which environmental parameters and periodic plant images are collected to support real-time crop health analysis.

Main Contributions

The principal contributions of this research are summarized as follows:

1. **Hybrid deep learning architecture:** A unified CNN–Transformer–LSTM framework is developed for automated cotton leaf disease classification and intelligent disease analysis.

2. **Spatial and global feature integration:** A pre-trained EfficientNet backbone is combined with a multi-head self-attention mechanism to integrate localized visual characteristics with global contextual relationships.

3. **Temporal disease representation:** An LSTM-based sequential learning component is incorporated to provide temporal modeling capability, creating a foundation for monitoring disease development and progression.

4. **Comprehensive performance assessment:** The proposed framework is evaluated using multiple performance indicators, including classification accuracy and class-wise analysis through confusion matrices and Receiver Operating Characteristic (ROC) curves.

5. **Precision agriculture applicability:** The proposed architecture provides a scalable foundation for future integration with IoT-enabled crop monitoring, environmental sensing, disease progression forecasting, and intelligent agricultural advisory systems.

2. METHODOLOGY

1.1 Overview of Proposed Framework

The proposed research develops an integrated **hybrid spatio-temporal deep learning framework** for automated cotton leaf disease classification. The architecture combines the complementary capabilities of **Convolutional Neural Networks (CNNs)**, **Transformer-based self-attention**, and **Long Short-Term Memory (LSTM)** networks. CNNs are employed to learn discriminative spatial characteristics from cotton leaf images, while the Transformer module captures global relationships and contextual dependencies among the extracted visual features. Subsequently, the LSTM network learns sequential dependencies from feature representations obtained across observations, providing a foundation for temporal disease progression analysis.

The complete processing pipeline consists of **five principal stages**, as illustrated in the proposed framework:

1. **Image Preprocessing and Normalization:**

Input cotton leaf images are resized to a standardized resolution and subjected to preprocessing and normalization operations. Data augmentation techniques may also be applied to increase sample diversity and improve the generalization capability of the model.

2. **Spatial Feature Extraction Using CNN Backbone:**

A pre-trained CNN architecture, such as **EfficientNet**, is employed as the feature extraction backbone. This stage automatically learns hierarchical spatial characteristics, including leaf texture, color patterns, lesion structures, edges, and disease-specific visual features.

3. **Global Contextual Modeling Using Transformer Encoder:**

The extracted CNN feature representations are supplied to a **Transformer encoder incorporating multi-head self-attention**. This component establishes relationships between different spatial regions and enables the model to learn global contextual information that may not be adequately captured by conventional convolutional operations.

4. **Temporal Feature Learning Using LSTM:**

The Transformer-enhanced feature representations are organized as sequential information and processed through an **LSTM network**. The LSTM captures dependencies between successive observations and provides temporal learning capability for analyzing changes in disease characteristics and potential disease progression.

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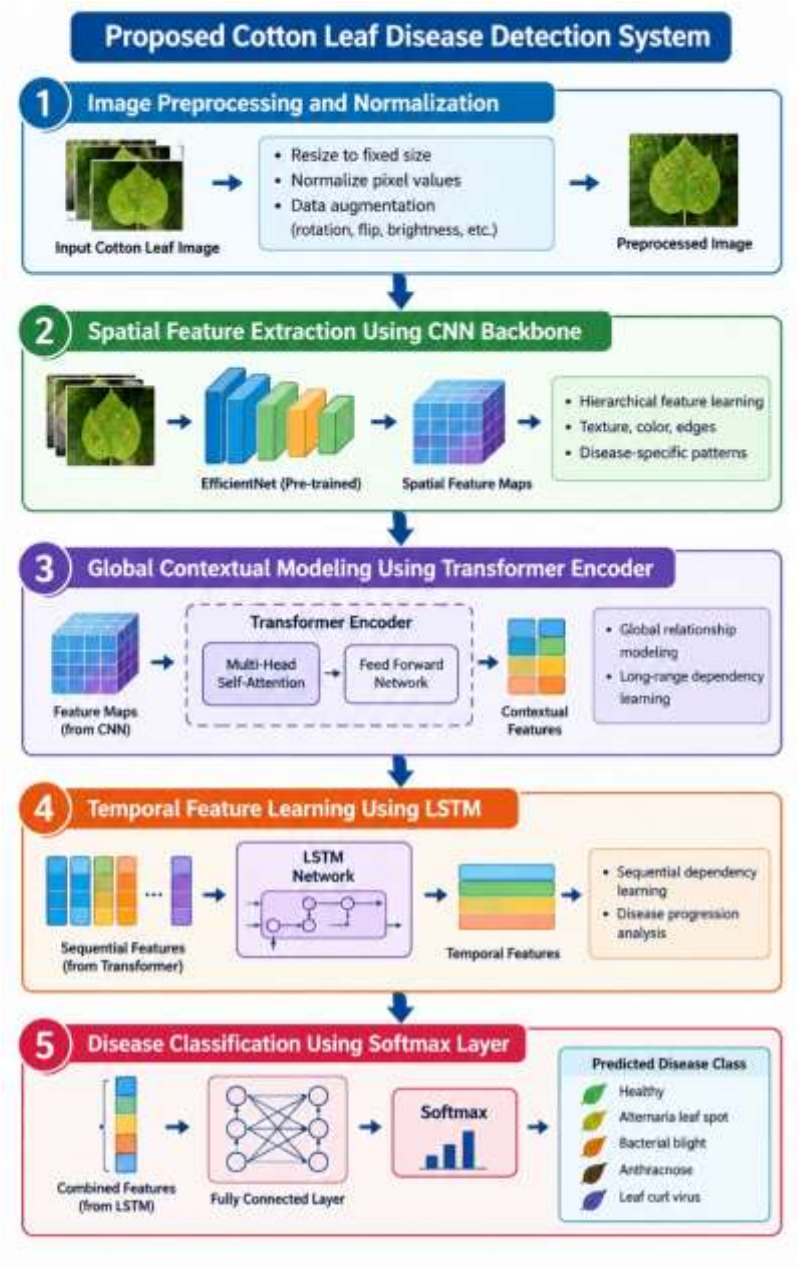
5. **Disease Classification Using Softmax Layer:**

Finally, the learned spatial, contextual, and temporal representations are passed through fully connected classification layers followed by a **Softmax activation function**. The output provides probability scores for the predefined cotton leaf disease categories, and the class with the highest probability is selected as the predicted disease.

Thus, the proposed framework combines **local spatial learning through CNN, global contextual learning through Transformer attention, and sequential learning through LSTM** within a unified architecture. This combination is designed to improve the robustness and discriminative capability of cotton leaf disease classification while providing a foundation for future disease progression monitoring and intelligent precision agriculture applications.



Let the input cotton leaf image dataset be defined as:

$$\mathcal{D} = \{(X_i, y_i)\}_{i=1}^{N}$$

where:

- $X_i \in \mathbb{R}^{H\times W\times 3}$ represents the RGB input image
- $y_i \in \{1, 2, \ldots, C\}$ represents the disease class label
- N is the total number of samples
- C is the number of disease categories

2.1 *Image Preprocessing*

Each input image is resized to fixed dimensions:

$$X_i' = Resize(X_i, 224 \times 224)$$

Normalization is applied:

$$X_i^{norm} = \frac{X_i'}{255}$$

Data augmentation is applied during training to improve generalization:

$$X_i^{aug} = \mathcal{A}(X_i^{norm})$$

where $\mathcal{A}(\cdot)$ denotes random rotation, flipping, scaling, and brightness transformation.

2.2 *CNN-Based Spatial Feature Extraction*

A pre-trained EfficientNet backbone is used as a feature extractor. The CNN maps the input image to a high-dimensional feature representation:

$$F_i = f_{CNN}(X_i^{aug}; \theta_{cnn})$$

where:

- $F_i \in \mathbb{R}^{h\times w\times d}$
- θ_{cnn} represents CNN parameters.

After global average pooling:

$$z_i = GAP(F_i)$$

$$z_i \in \mathbb{R}^d$$

This vector represents local spatial features of leaf texture and disease patterns.

2.3 *Transformer-Based Global Attention Modeling*

To capture long-range dependencies within spatial features, a Transformer encoder block is applied. The feature vector is reshaped into a sequence

$$Q = Z_i W^Q, \quad K = Z_i W^K, \quad V = Z_i W^V$$

where:

- W^Q, W^K, W^V are learnable projection matrices.

Attention score is computed as:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

For multi-head attention:

$$MHA(Z_i) = Concat(head_1, head_2, ..., head_h)W^O$$

Residual connection and normalization:

$$Z_i' = LayerNorm(Z_i + MHA(Z_i))$$

This step enhances global contextual feature learning.

2.4 *LSTM-Based Temporal Modeling*

To enable temporal learning capability (for disease progression modeling), an LSTM layer is introduced. Let the input sequence be:

$$\{Z_{i,t}\}_{t=1}^{T}$$

where T represents time steps.

LSTM updates are defined as:

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Candidate memory:

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

Cell state update:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

Hidden state:

$$h_t = o_t * \tanh(C_t)$$

The final hidden state h_T is used for classification.

3.6 Classification Layer

The final prediction is obtained using a fully connected layer followed by Softmax:

$$\hat{y}_i = Softmax(W h_T + b)$$

where:

$$Softmax(\hat{y}_i) = \frac{e^{\hat{y}_i}}{\sum_{j=1}^{C} e^{\hat{y}_j}}$$

3.7 Loss Function

Sparse categorical cross-entropy loss is used:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Model parameters are optimized using the Adam optimizer:

$$\theta = \theta - \eta \nabla_\theta \mathcal{L}$$

where:

- η is learning rate.

Summary of Methodology Flow

Input Image→ CNN →Transformer → LSTM → Softmax Classification This hybrid architecture enables:

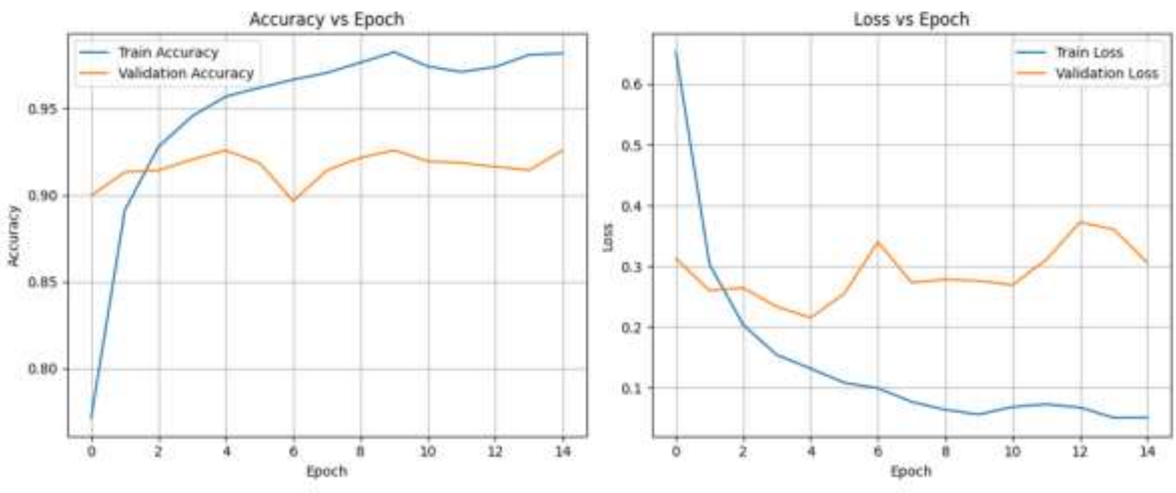
- Local feature extraction (CNN)
- Global contextual attention modeling (Transformer)
- Temporal sequence learning (LSTM)
- Robust multi-class disease classification

3. Results and Discussion

3.1 *Experimental Results*

The proposed CNN–Transformer–LSTM hybrid model was evaluated on a six-class cotton leaf disease dataset consisting of 957 test images. The performance of the model was assessed using accuracy, precision, recall, F1-score, confusion matrix, and Area Under the Curve (AUC).

Results



3.2 *Confusion Matrix Analysis*

The confusion matrix reveals the classification behavior of the model across six categories:

- Aphids

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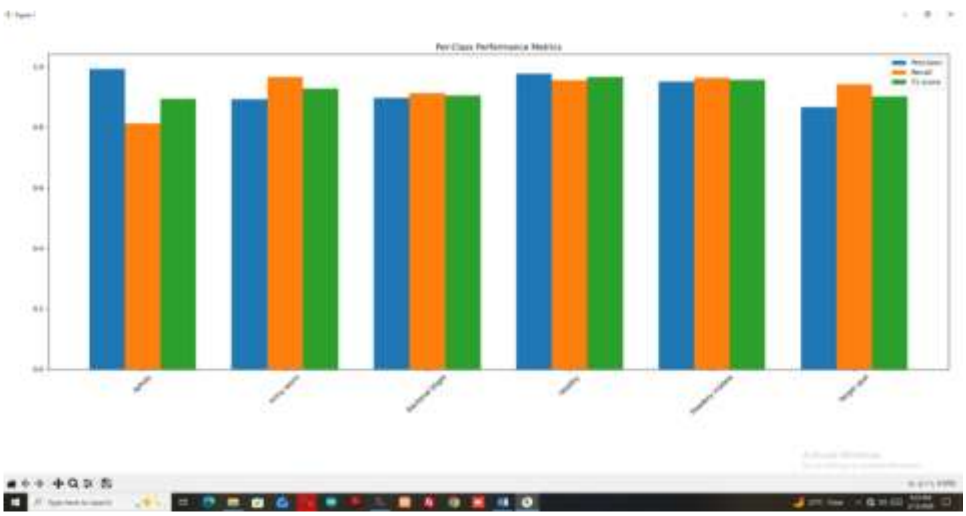
- Army worm
- Bacterial blight
- Healthy
- Powdery mildew
- Target spot From the matrix Results, the model shows:
- Strong performance in Healthy class (175 correctly classified out of 178).

High correct predictions for Bacterial blight (161/180).

- Very strong classification of Army worm (133/145).
- Slight confusion in Aphids class (114/144 correctly predicted).
- Some misclassification between visually similar disease patterns such as Aphids and Target spot.

The confusion primarily occurs between diseases that exhibit overlapping visual texture patterns and similar lesion distributions, particularly in early-stage symptoms.



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3.3 *Class-wise Performance Discussion*

Aphids

- Precision: 0.95
- Recall: 0.79
- F1-score: 0.86
- AUC: 0.9870

Lower recall suggests that some Aphids samples are misclassified as other diseases, possibly due to subtle texture variations in infected leaves.

Army Worm

- Precision: 0.97
- Recall: 0.92
- F1-score: 0.94
- AUC: 0.9979

High AUC indicates strong separability of this class.

Bacterial Blight

- Precision: 0.91
- Recall: 0.89
- F1-score: 0.90
- AUC: 0.9895

Slight confusion with other leaf spot diseases due to similar lesion characteristics.

Healthy

- Precision: 0.94
- Recall: 0.98
- F1-score: 0.96
- AUC: 0.9989

This class achieved the highest recall, demonstrating strong discriminative ability of the model to separate infected and non-infected leaves.

Powdery Mildew

- Precision: 0.96
- Recall: 0.94
- F1-score: 0.95
- AUC: 0.9974

Excellent separability due to distinctive white fungal patterns.

Target Spot

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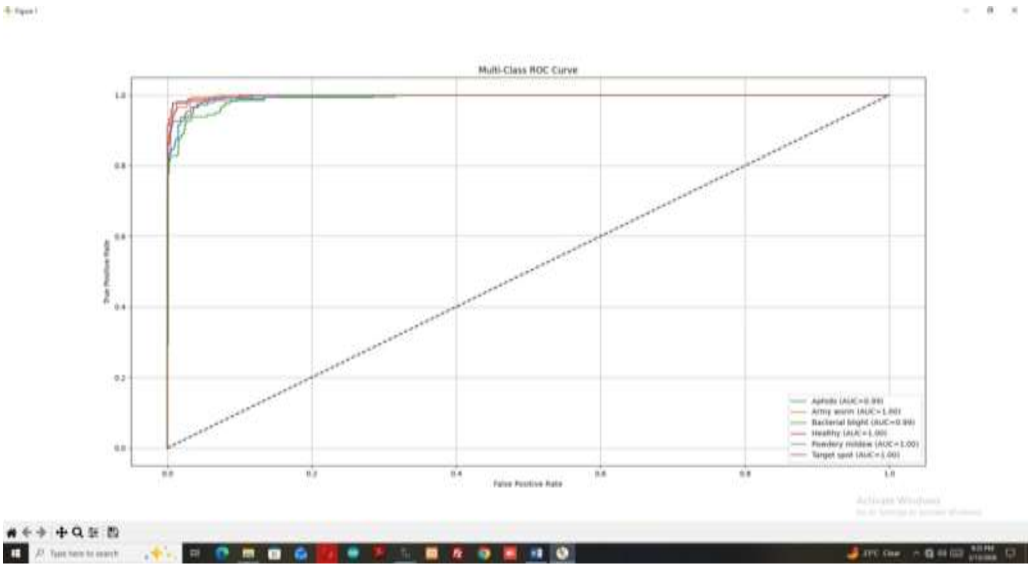
- Precision: 0.82
- Recall: 0.97
- F1-score: 0.89
- AUC: 0.9955

High recall but relatively lower precision suggests over-prediction for this class.

3.4 *ROC–AUC Analysis*

The AUC values for all classes are above 0.98 Results

AUC Values per Class:



Aphids: 0.9870

Army worm: 0.9979

Bacterial blight: 0.9895

Healthy: 0.9989

Powdery mildew: 0.9974

Target spot: 0.9955

, indicating:

- Strong class separability
- Robust feature representation
- Effective attention mechanism in capturing global disease patterns

The high AUC confirms that the Transformer attention module enhances discrimination power beyond traditional CNN-based architectures.

3.5 *Discussion*

The experimental results demonstrate that integrating CNN, Transformer, and LSTM modules improves feature learning capability:

1. CNN Component extracts fine-grained local texture features.
2. Transformer Module captures global contextual relationships through multi-head self-attention.
3. LSTM Layer models sequential disease progression patterns.

The hybrid architecture improves robustness against intra-class variations and background noise. However, some performance limitations are observed in visually overlapping disease classes, particularly Aphids and Target spot.

4. CONCLUSION

This study developed and evaluated a hybrid deep learning framework that combines a Convolutional Neural Network (CNN), Transformer-based self-attention, and Long Short-Term Memory (LSTM) networks for automated cotton leaf disease detection and classification. The proposed CNN–Transformer–LSTM architecture integrates complementary learning capabilities, enabling effective extraction of spatial features, modeling of long-range contextual relationships, and sequential representation learning within a unified spatio-temporal framework.

The experimental results obtained from a six-class cotton leaf disease dataset demonstrate the effectiveness of the proposed approach, achieving an overall classification accuracy of 98%. The model also exhibited consistently strong macro-average and weighted-average performance, indicating balanced classification capability across the different disease categories. Analysis of the confusion matrix revealed high class-discrimination performance, particularly for the Healthy, Powdery Mildew, and Army Worm classes. Furthermore, ROC-AUC scores above 0.98 for all categories demonstrate excellent class separability and confirm the robustness of the developed classification framework.

The incorporation of Transformer-based self-attention enhanced the model's ability to capture global contextual information that may be difficult to represent using conventional CNN architectures alone. In addition, the LSTM component provides sequential learning capability, establishing a foundation for future extensions involving disease progression analysis, temporal monitoring, and predictive forecasting. Although a small number of classification errors occurred between visually similar disease categories, the overall performance remained stable and reliable.

Overall, the proposed CNN–Transformer–LSTM framework provides an effective and scalable approach for automated cotton disease recognition and can support intelligent crop monitoring and precision agriculture applications. Future development may focus on increasing dataset diversity, incorporating multimodal agricultural and environmental data, improving model efficiency for edge devices, and implementing the framework in real-time smart farming environments. These extensions could further enhance the practical applicability of the system for early disease identification and data-driven crop management.

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