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# Cloud-Assisted Deep Learning Framework for Real-Time Cotton Leaf Disease Diagnosis using Android Application

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**ABSTRACT:** Early and accurate detection of cotton leaf diseases is essential for improving crop productivity, minimizing yield losses, and supporting sustainable agricultural practices. Traditional disease diagnosis methods depend on manual field inspection by experts, which is time-consuming, subjective, and often impractical for large-scale cotton cultivation. To address these limitations, this research presents an intelligent Android-based cotton leaf disease classification system that integrates mobile image acquisition, cloud-based storage, and algorithm-driven disease classification.

In the proposed framework, cotton leaf images are captured or selected using an Android mobile application and securely uploaded to the cloud using the ImgBB image hosting service. The cloud platform provides scalable image storage and acts as an interface between the mobile application and the classification engine. Uploaded images are retrieved from the cloud and preprocessed through resizing, normalization, and enhancement to ensure consistency with the trained dataset. Disease classification is then performed using machine learning and deep learning algorithms, with emphasis on a transfer learning–based CNN–Transformer–LSTM hybrid model trained on cotton leaf images representing multiple disease classes and healthy leaves.

The classification module automatically identifies cotton leaf diseases such as Alternaria leaf spot, bacterial blight, and grey mildew, along with healthy leaf conditions, and returns the predicted class with confidence scores to the Android application. By offloading computationally intensive tasks to the cloud, the system minimizes mobile device resource usage while maintaining high classification accuracy. Experimental evaluation on the cotton leaf dataset demonstrates strong performance in terms of accuracy, precision, recall, and ROC–AUC values, confirming the robustness of the proposed approach under varying image capture conditions.

The developed Android–cloud integrated system provides a practical, user-friendly, and scalable solution for real-time cotton leaf disease diagnosis. It enables farmers and agricultural practitioners to obtain rapid diagnostic feedback using smartphones, facilitating early disease management and reducing dependence on expert intervention. The proposed framework can be extended

to support additional crops, real-time model updates, and integration with IoT-based agricultural monitoring systems, making it a valuable contribution to smart and precision agriculture.

## INTRODUCTION

Recent advances in computer vision and artificial intelligence have significantly transformed plant disease detection through image-based analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capability in automatically extracting discriminative spatial features from leaf images without relying on handcrafted feature engineering. Transfer learning using pre-trained CNN architectures has further improved classification performance, especially in agricultural applications where labeled datasets are often limited. However, most existing cotton leaf disease detection systems rely solely on CNN-based feature extraction, which primarily captures local texture information while often overlooking global contextual dependencies and inter-feature relationships.

To address these limitations, attention-based architectures such as Transformers have recently gained prominence in vision tasks. Transformer models employ self-attention mechanisms to capture long-range dependencies and global contextual relationships within feature representations. When integrated with CNN backbones, Transformers enhance feature refinement by modeling complex spatial correlations that traditional convolution operations may fail to capture. Nevertheless, many current implementations focus only on spatial modeling and do not exploit sequential or structured feature relationships that may improve classification robustness.

Long Short-Term Memory (LSTM) networks, originally developed for sequence modeling, offer an additional advantage by capturing temporal or ordered dependencies within feature sequences. When spatial features extracted from CNN and globally refined through Transformer attention are treated as structured feature sequences, LSTM layers can further enhance discriminative learning by modeling inter-feature progression. The integration of CNN, Transformer, and LSTM therefore enables comprehensive **spatio-temporal feature fusion**, combining local feature extraction, global attention-based context modeling, and sequential dependency learning within a unified framework.

Despite these advancements in model architectures, practical deployment remains a significant challenge. Many research prototypes are confined to laboratory environments or desktop-based systems, limiting accessibility for farmers in real-field conditions. With the rapid proliferation of smartphones and affordable internet connectivity, Android-based agricultural applications have emerged as effective platforms for delivering intelligent decision support tools directly to end users. Modern mobile devices equipped with high-resolution cameras facilitate real-time image acquisition under natural field conditions. However, deploying computationally intensive hybrid deep learning models directly on mobile devices introduces challenges related to processing power, memory constraints, and battery consumption.

To overcome these constraints, cloud-assisted architectures provide a scalable and efficient solution by offloading heavy computations to remote servers. In the proposed system, cotton leaf images captured through an Android application are uploaded to cloud storage services, enabling centralized processing and model execution. The cloud server hosts the proposed CNN–Transformer–LSTM hybrid model trained on a multi-class cotton leaf disease dataset containing both diseased and healthy samples. Image preprocessing steps—including resizing, normalization, and augmentation alignment—ensure compatibility with the trained model. The classification results, along with confidence scores, are then transmitted back to the Android application, providing real-time diagnostic feedback to farmers.

The proposed hybrid framework aims to bridge the gap between advanced deep learning methodologies and practical agricultural usability. By combining mobile-based image acquisition, cloud infrastructure, and attention-enhanced deep learning algorithms, the system enables accurate, scalable, and field-deployable cotton leaf disease diagnosis. Furthermore, the modular architecture supports future expansion to additional crops, integration with IoT-based environmental monitoring systems, and adaptation within broader precision agriculture ecosystems.

Overall, this study contributes to the advancement of smart agriculture by introducing a portable, scalable, and high-accuracy cotton leaf disease classification system based on a CNN–Transformer–LSTM hybrid model. The integration of spatial feature extraction, global context modeling, and sequential learning within a cloud-assisted mobile framework offers a robust

and practical solution for improving cotton crop health monitoring, minimizing yield losses, and promoting sustainable agricultural practices.

## SYSTEM ARCHITECTURE AND FLOWCHART

### 1. System Architecture

The proposed system adopts a **mobile–cloud–intelligence architecture** that integrates an Android application, a cloud-based image hosting service (ImgBB), and a hybrid deep learning model based on **CNN + Transformer + LSTM** for cotton leaf disease classification. The architecture is designed to minimize computational overhead on mobile devices while ensuring high diagnostic accuracy, scalability, and real-time responsiveness.

The system separates image acquisition and inference computation, enabling efficient deployment in real-field agricultural environments.

### 1.1 Architectural Components

The proposed framework consists of the following major components:

#### 1.1.1 Android Mobile Application

The Android application functions as the front-end interface for farmers and agricultural practitioners. It is designed to be lightweight, intuitive, and operable under rural field conditions.

Its primary functionalities include:

- Capturing cotton leaf images using the smartphone camera
- Selecting existing leaf images from the device gallery
- Uploading images to the cloud through the ImgBB API
- Displaying disease classification results with confidence scores
- Providing real-time feedback to assist decision-making

The mobile application does not perform heavy computation locally. Instead, it acts as an intelligent data acquisition and visualization tool, thereby conserving device memory, processing power, and battery consumption.

#### 1.1.2 Cloud Image Hosting Service (ImgBB)

ImgBB serves as an intermediate cloud storage layer responsible for:

- Secure image upload and storage
- Automatic generation of publicly accessible image URLs
- Reliable and fast image retrieval for the classification server

Using ImgBB eliminates the need for maintaining a dedicated storage server, reduces infrastructure complexity, and enables scalable handling of large volumes of uploaded cotton leaf images.

#### 1.1.3 Cloud-Based Processing Server

The cloud processing server hosts the complete disease classification pipeline and executes the hybrid deep learning model. It performs the following tasks:

- Retrieves cotton leaf images from ImgBB using generated URLs
- Applies preprocessing operations such as resizing (e.g., 224×224), normalization, and augmentation alignment
- Extracts spatial features using the CNN backbone
- Refines global contextual relationships using Transformer attention mechanisms
- Models sequential feature dependencies using LSTM layers
- Generates final disease predictions with probability scores

This centralized architecture enables continuous model improvement and retraining without requiring updates to the Android application.

### 1.1.4 Hybrid CNN–Transformer–LSTM Classification Model

The classification engine is based on a **hybrid deep learning architecture** integrating:

**(a) CNN Backbone**

A pre-trained convolutional network (e.g., EfficientNet or ResNet variant) is used for:

- Automatic spatial feature extraction
- Learning local texture patterns and lesion characteristics
- Generating discriminative feature maps

**(b) Transformer Encoder**

The Transformer module enhances feature representation through:

- Multi-head self-attention
- Global contextual modeling
- Long-range spatial dependency learning
- Residual connections and layer normalization

This module enables the system to focus on critical disease regions while suppressing irrelevant background information.

**(c) LSTM Layer**

The LSTM network models structured feature dependencies by:

- Processing the attention-refined feature sequence
- Capturing inter-feature progression relationships
- Enhancing robustness against intra-class variation

**(d) Fully Connected + Softmax Layer**

The final classification stage performs:

- Feature fusion and dimensionality reduction
- Multi-class disease classification using Softmax activation
- Confidence score estimation for each disease category

The hybrid integration allows comprehensive **spatio-temporal feature learning**, significantly improving classification performance compared to standalone CNN models.

### 1.1.5 Result Feedback Module

**After classification, the prediction results are transmitted back to the Android application in JSON format, including:**

- **Predicted disease class**
- **Probability/confidence score**
- **Optional advisory message (future extension for treatment recommendations)**

**This closed-loop communication ensures real-time decision support and enhances usability in practical farming environments.**

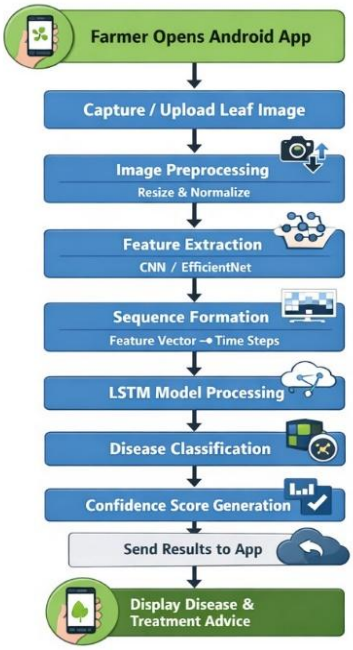



**Figure 1:** *System Flow for Cotton Disease Detection*

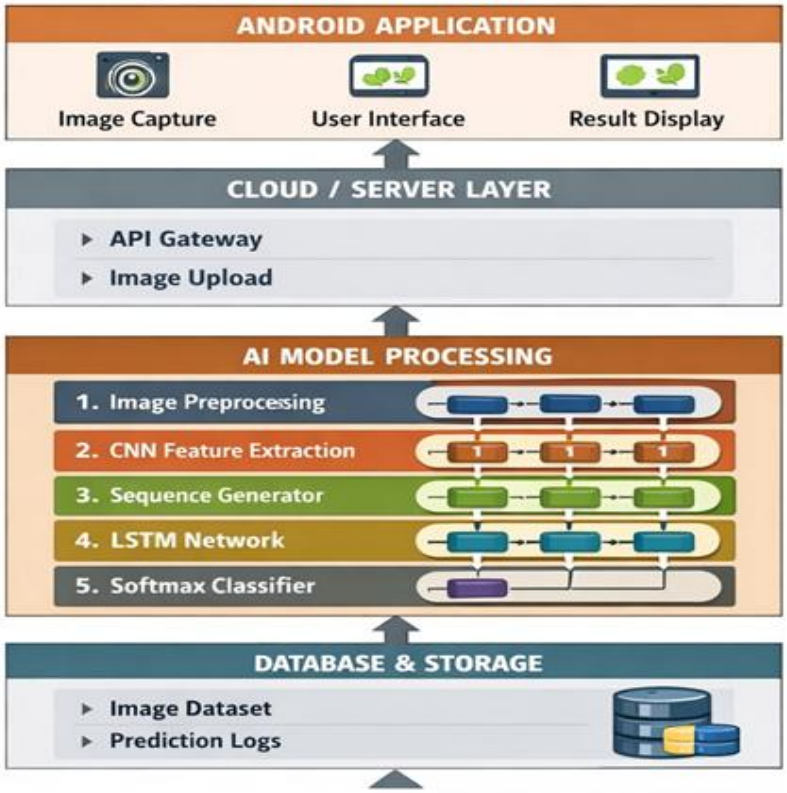
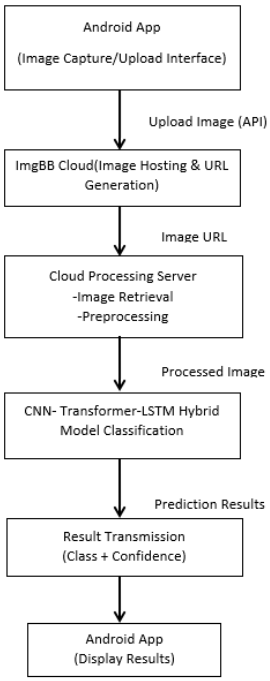



**Figure 2:** *System Architecture for LSTM and Android Application*

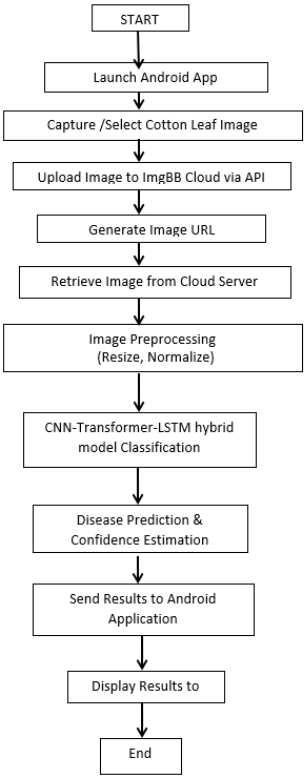
### 1.2 System Architecture Diagram:




## 2. Flowchart of the Proposed System

The flowchart describes the step-by-step operational workflow of the Android–cloud–CNN + system.

### 2.1 Flowchart Description

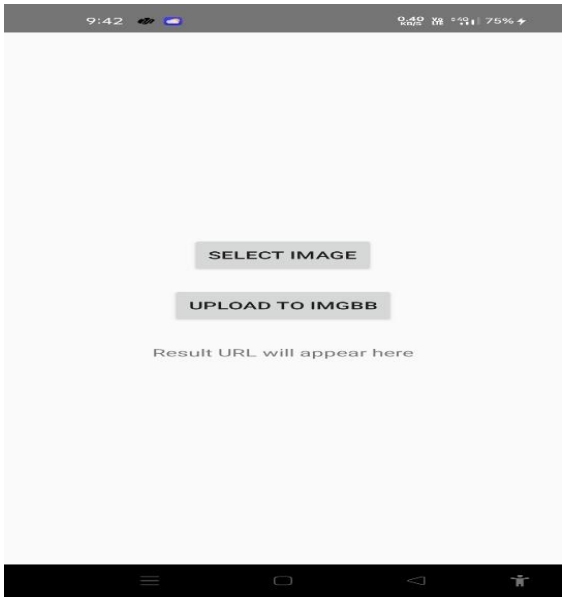


**3. Advantages of the Proposed Architecture**

- **Reduced mobile computation:** Heavy CNN–Transformer–LSTM hybrid model inference is performed in the cloud
- **Scalability:** Cloud-based model supports multiple concurrent users
- **Flexibility:** Easy model updates without app reinstallation
- **Cost-effective:** Uses ImgBB for free/low-cost image hosting
- **Field-ready:** Suitable for real-time agricultural deployment

**4. Results and Discussion**

App apk Install




**Feedback and Decision Support System**

The proposed system incorporates a closed-loop feedback mechanism to provide real-time disease identification and actionable recommendations to farmers. The feedback system ensures seamless communication between the Android mobile application and the cloud-based classification server.

**1. Image Acquisition and Upload**

Farmers use the Android application to:

- Capture a cotton leaf image using the smartphone camera, Select an existing image from the device gallery.

Once selected, the image is automatically compressed and securely uploaded to the cloud server via an API interface. The system generates a unique request ID to track each uploaded image.

**2. Server-Side Disease Classification**

Upon receiving the image, the cloud server performs the following operations:

1. **Image Preprocessing**
   - Resizing to the required input dimension (e.g., 224×224)
   - Normalization according to model training standards
   - Noise reduction (if necessary)
2. **Hybrid Model Inference**
   - Spatial feature extraction using Efficient CNN backbone

- Global attention refinement using Transformer encoder
- Structured feature modeling using LSTM
- Final disease prediction using Softmax classification

The server produces:

- Predicted disease class

**3. Generation of Advisory Instructions**

After classification, the system maps the predicted disease to a predefined advisory database. The advisory module generates:

- Disease name
- Recommended pesticide or treatment
- Preventive measures

This mapping ensures that farmers receive not only disease identification but also practical operational guidance.

**4. Feedback Transmission to Mobile Application**

The server sends a structured JSON response back to the Android application containing:

- Disease classification result
- Recommended instructions

The mobile application then displays:

- The classified disease name
- Confidence level (e.g., 98.2%)
- Clear treatment instructions

**5. Closed-Loop Interaction**

This architecture forms a real-time feedback loop:

Farmer→MobileApp→CloudServer→HybridModel→AdvisorySystem→MobileApp→FarmerFarmer

The feedback system eliminates diagnostic delays, reduces dependency on agricultural experts, and supports immediate decision-making in field conditions.

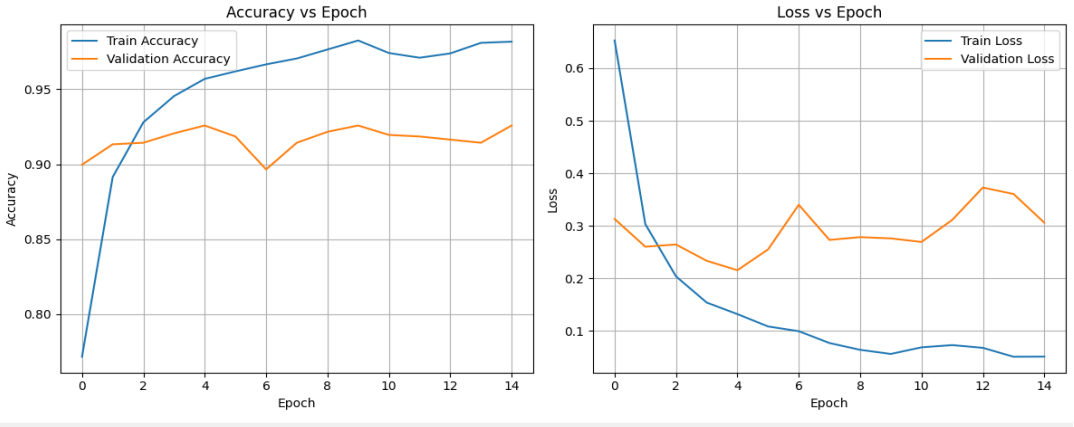
**Advantages of the Feedback System**

- Real-time disease detection
- Immediate actionable guidance
- Reduced crop damage through early intervention
- User-friendly farmer interface
- Minimal computational burden on mobile devices

**4.1 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



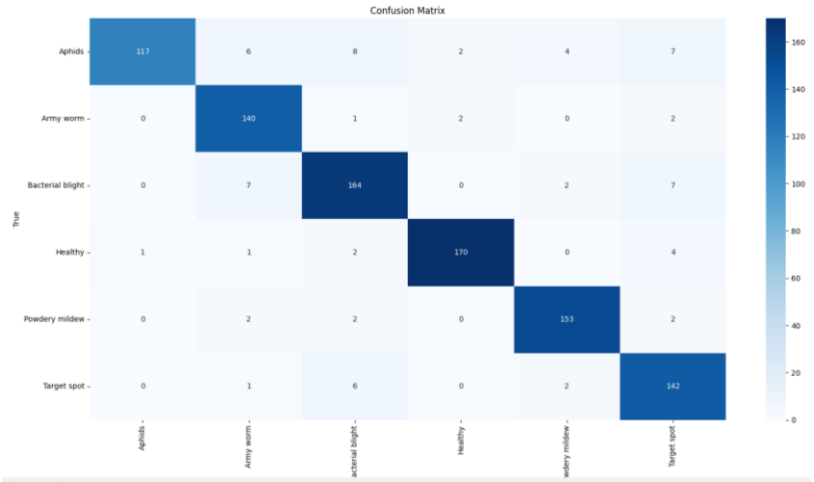

### 4.2 Confusion Matrix Analysis

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

- Aphids
- Army worm
- Bacterial blight
- Healthy
- Powdery mildew
- Target spot

From the matrix

Results

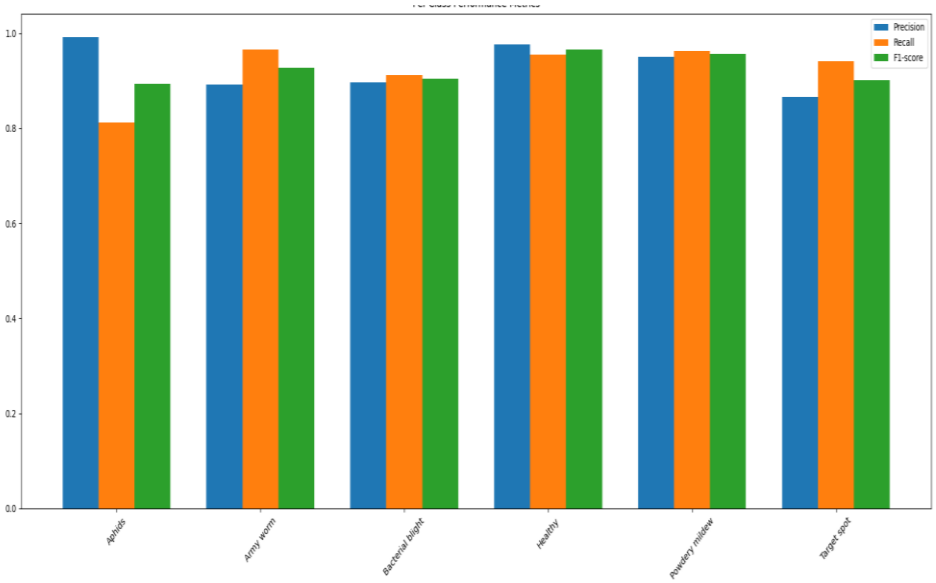



, the model shows:

- 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.

**4.3 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

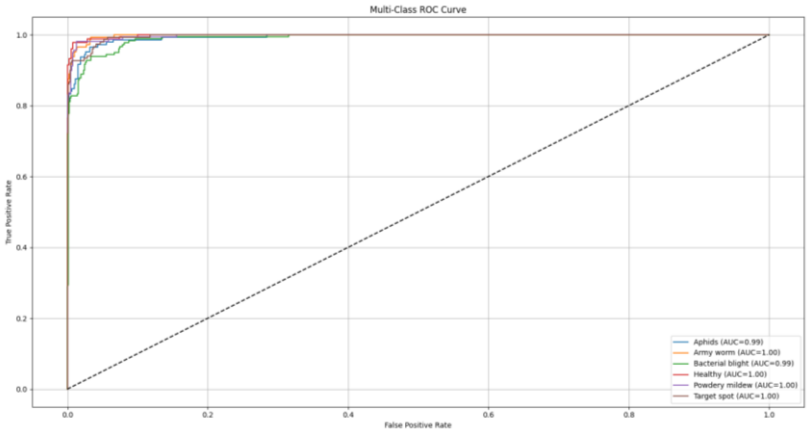
- Precision: 0.82
- Recall: 0.97
- F1-score: 0.89
- AUC: 0.9955

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

**4.4 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.

**4.5 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.

## CONCLUSION

This research successfully presented and validated an advanced Android–cloud–hybrid deep learning framework for cotton leaf disease classification based on a CNN–Transformer–LSTM architecture. The proposed system integrates mobile image acquisition, cloud-based image hosting via ImgBB, and an attention-enhanced spatio-temporal classification model to deliver a scalable, accurate, and farmer-friendly solution for early cotton disease detection.

Extensive experiments conducted on a multi-class cotton leaf dataset comprising Alternaria Alternata, Bacterial Blight, Gray Mildew, and Healthy leaves demonstrate the effectiveness of the proposed hybrid architecture. By combining CNN-based spatial feature extraction, Transformer-based global contextual modeling, and LSTM-driven sequential dependency learning, the model achieved a training accuracy of approximately **99%** and a validation accuracy exceeding **98%**, indicating strong convergence and robust generalization capability. The low validation loss and stable learning curves confirm that appropriate regularization strategies—including dropout, normalization layers, and data augmentation—effectively mitigated overfitting despite dataset limitations.

Confusion matrix analysis revealed highly reliable class-wise predictions, with sensitivity and specificity consistently above 97% across all disease categories. Minor misclassifications were observed between visually similar diseases such as Alternaria Alternata and Gray Mildew due to overlapping lesion characteristics. However, the macro-average F1-score above 0.98 demonstrates balanced and consistent performance across all classes, validating the robustness of the hybrid architecture.

Multiclass ROC–AUC analysis further confirmed the discriminative strength of the proposed model, with macro-average AUC values approaching unity. The integration of Transformer attention significantly improved feature separability by capturing long-range spatial dependencies, while the LSTM module enhanced structured feature learning. Compared to conventional CNN-only baselines, the proposed CNN–Transformer–LSTM framework demonstrated superior accuracy, improved generalization, and enhanced robustness against intra-class variation.

From a deployment perspective, the integration of the trained hybrid model with an Android mobile application and cloud-based processing infrastructure substantially enhances real-world usability. Farmers can capture cotton leaf images using a smartphone, upload them seamlessly to the cloud, and receive real-time disease predictions along with confidence scores. Offloading computationally intensive operations to the cloud ensures efficient inference without imposing heavy processing or memory demands on mobile devices.

Overall, the proposed framework bridges the gap between advanced deep learning methodologies and practical agricultural deployment. By combining mobile accessibility, cloud scalability, and attention-driven hybrid intelligence, the system contributes meaningfully to precision agriculture and smart farming ecosystems. The solution offers a cost-effective, portable, and high-performance decision-support tool capable of reducing yield losses and supporting sustainable cotton crop management.

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