CottonLeafNet-Pilot: A Lightweight Hybrid CNN–Transformer Framework for Integrated Cotton Disease Detection and Growth Stage Monitoring

Rinkesh N. Parmar
S.S. Agrawal College of Commerce and Management, Navsari
(Affiliated to Veer Narmad South Gujarat University, Surat)

P.D. Joshi
Veer Narmad South Gujarat University, Surat

ABSTRACT

Cotton is one of the most important crops in India and plays a vital role in the agricultural and textile economy. However, cotton productivity is frequently affected by plant diseases such as leaf spot, wilt, boll rot, and bacterial blight, which lead to significant yield loss and increased dependence on chemical pesticides. In addition to disease detection, understanding the growth stage of the crop is equally important for effective crop management and decision-making. Early identification of both disease conditions and plant development stages can support timely agricultural interventions.

This paper presents CottonLeafNet-Pilot, a lightweight hybrid CNN–Transformer framework designed for integrated cotton disease detection and growth stage monitoring. The proposed architecture combines convolutional neural networks for local feature extraction with attention-based transformer modules for capturing global contextual relationships. The model also incorporates attention mechanisms to focus on disease-affected regions while suppressing irrelevant background information.

The framework is trained and evaluated on a curated dataset of 6,000 cotton leaf images collected under diverse field conditions. Experimental results demonstrate an overall classification accuracy of 96.2% with a macro F1-score of 95.9%, while maintaining a lightweight architecture suitable for deployment on mobile and edge devices.

The study demonstrates the feasibility of developing indigenous AI solutions for precision agriculture, enabling integrated monitoring of cotton crop health and development stages. The proposed approach supports sustainable farming practices and contributes to the vision of ATMANIRBHAR BHARAT in agricultural technology.

Keywords

Cotton disease detection, Growth stage classification, Hybrid CNN–Transformer, Deep learning, Precision agriculture, Explainable AI

1. INTRODUCTION

Cotton is one of the most important cash crops in India and plays a significant role in the agricultural and textile economy. It supports the livelihood of millions of farmers and contributes substantially to the national income through textile production and exports. However, cotton productivity is often affected by various plant diseases such as leaf spot, wilt, boll rot, and bacterial blight. These diseases reduce fiber yield and quality, increase cultivation costs, and often lead to excessive use of chemical pesticides. Early and accurate identification of these diseases is therefore essential to ensure sustainable crop management and minimize economic losses [1], [4], [5].

In addition to disease monitoring, identifying cotton plant growth stages is important for effective agricultural management. Cotton crops progress through stages such as seedling, vegetative growth, flowering, boll formation, and maturity, each requiring specific practices including irrigation, fertilizer application, and pest control. Accurate growth stage identification can support better crop management and improve overall productivity [24], [25].

Traditional crop monitoring methods rely heavily on manual field inspection by agricultural experts. Although effective at small scales, this approach is time-consuming, subjective, and difficult to implement across large agricultural areas. Recent advancements in computer vision and deep learning have enabled automated plant disease detection using image-based analysis. Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting visual features related to leaf texture, lesion patterns, and color variations associated with plant diseases [2], [9], [17]. More recently, transformer-based architectures have been introduced to capture global contextual relationships within images through attention mechanisms [10], [12], [20].

Combining CNNs and transformer modules provides a powerful hybrid approach for agricultural image analysis. CNN layers efficiently extract local disease features, while transformer attention captures global structural patterns across the plant. Hybrid CNN–Transformer models have shown improved performance in plant disease detection by leveraging both local and global feature representations [11], [15], [19]. Despite these advancements, many existing approaches rely on large pre-trained models and extensive datasets, which limits their practical applicability in resource-constrained agricultural environments.

To address these challenges, this paper presents CottonLeafNet-Pilot, a lightweight hybrid CNN–Transformer framework for integrated cotton disease detection and growth stage monitoring. The proposed architecture combines convolutional feature extraction, attention mechanisms, and transformer-based global context modelling to achieve accurate classification while maintaining computational efficiency. The model is trained and evaluated on a curated dataset of cotton leaf images collected from Indian cotton-growing regions under real field conditions.

The main contributions of this study are summarized as follows:

1. Development of a lightweight hybrid CNN–Transformer architecture for cotton crop monitoring.
2. Accurate detection of major cotton diseases using image-based deep learning.
3. Extension of the framework toward growth stage classification for lifecycle crop monitoring.
4. Demonstration of an efficient and deployable AI solution aligned with the vision of ATMANIRBHAR BHARAT in agricultural technology.

2. RELATED WORK

Automated plant disease detection and crop growth monitoring have attracted significant research attention due to their potential to enable timely interventions, reduce excessive pesticide usage, and improve crop yield. This section reviews prior work in deep learning–based plant disease detection, plant growth stage monitoring, vision transformer approaches, and hybrid CNN–Transformer models, and identifies the research gap addressed by CottonLeafNet-Pilot.

Convolutional Neural Networks (CNNs) have emerged as the dominant approach for image-based plant disease detection because of their ability to automatically learn hierarchical visual features. Numerous studies have applied CNNs to crops such as tomato, rice, maize, and cotton. **Aslam et al. (2025)** proposed multi-CNN architectures for cotton leaf disease detection and achieved high classification accuracy across multiple disease categories. **Kaur et al. (2025)** introduced explainable CNN models for cotton leaves using Grad-CAM to visualize disease-affected regions, improving model interpretability. **Sharma et al. (2024)** demonstrated that lightweight CNN architectures can achieve competitive performance for maize leaf disease detection. Transfer learning has also been widely explored; **Patel et al. (2023)** used pre-trained ResNet50 and VGG16 models for rice leaf disease detection, reporting accuracy above 95 percent. **Gupta et al. (2024)** further showed that ensemble CNN approaches enhance robustness across different cotton disease classes.

In addition to disease detection, computer vision techniques have also been applied to plant growth stage monitoring. Crop growth stages represent important physiological phases of plant development and provide critical information for agricultural management practices such as irrigation scheduling, fertilizer application, and pest control. Image-based phenotyping approaches have been increasingly used to identify plant growth stages using deep learning models. **Abdullah et al. (2025)** proposed a deep learning framework for cotton seedling monitoring and growth stage classification, demonstrating that convolutional networks can effectively identify plant developmental stages from field images. Similarly, **Wang et al. (2019)** developed a CNN-based approach for cotton growth period recognition using morphological features extracted from crop images. These studies highlight the feasibility of using computer vision for automated crop phenology monitoring.

Despite their success, CNN-based methods have notable limitations. Convolutional operations primarily focus on local feature extraction and may struggle with capturing global context or distinguishing visually similar patterns that differ subtly in spatial relationships. Additionally, high-performing CNN models often contain millions of parameters, posing challenges for deployment in resource-constrained agricultural environments.

Vision Transformers (ViTs) have recently been applied to plant disease detection due to their ability to model long-range dependencies using self-attention mechanisms. **Li et al. (2023)** applied ViTs to tomato leaf disease datasets, demonstrating improved capability for capturing global relationships within plant images. **Wang et al. (2024)** further combined transformer models with data augmentation techniques for maize disease detection. However, transformer-based models typically require large datasets and significant computational resources, which can limit their effectiveness in agricultural applications where labelled datasets are often limited.

To overcome these challenges, hybrid CNN–Transformer architectures have been proposed to combine the advantages of both approaches. **Singh et al. (2023)** introduced ConvTransNet-S, integrating CNN feature extraction with lightweight transformer blocks for plant disease recognition. **Zhou et al. (2023)** proposed FOTCA, which combines CNNs with adaptive Fourier neural operators to capture both local and global features. **Li and Chen (2024) and Rao et al. (2024)** demonstrated that hybrid models consistently outperform standalone CNN architectures in plant disease classification tasks. These findings motivate the development of efficient hybrid models for agricultural image analysis.

2.1 Research Gap

Despite recent progress, several limitations remain in existing plant disease detection and crop monitoring approaches. Many hybrid and transformer-based methods assume the availability of large-scale datasets, limiting their applicability to localized agricultural contexts. High computational requirements and model size also hinder deployment in resource-constrained rural environments. Furthermore, most existing studies focus either on disease detection or on growth stage monitoring independently, with limited research addressing integrated crop monitoring systems.

These challenges motivate the development of CottonLeafNet-Pilot, a lightweight hybrid CNN–Transformer framework designed to perform effectively on moderate datasets while balancing accuracy and computational efficiency. The proposed framework aims to provide an indigenous foundation for scalable AI-based cotton disease detection with potential extension toward integrated growth stage monitoring in Indian agricultural environments.

3. METHODOLOGY

The proposed CottonLeafNet-Pilot framework is designed as a lightweight hybrid deep learning architecture for cotton disease detection and growth stage classification. The system combines convolutional neural networks (CNNs), attention mechanisms, and transformer modules to capture both local lesion features and global structural patterns of plant leaves. The overall pipeline includes dataset preparation, preprocessing, feature extraction, attention modelling, and classification.

3.1 Dataset Collection

A curated dataset of 6,000 cotton leaf images was prepared for this study. The dataset contains images collected from agricultural farms and research stations across cotton-growing regions in India, captured under different lighting conditions and backgrounds to simulate real field environments. The dataset was labelled into five disease classes: Healthy, Leaf Spot, Wilt, Boll Rot, and Bacterial Blight.

Each class contains approximately 1,200 images, ensuring balanced class distribution and reducing model bias during training. To support growth stage identification, images representing different cotton plant development stages were also considered, including seedling, vegetative growth, flowering, boll formation, and maturity.

3.2 Region-Aware Preprocessing

Before model training, several preprocessing operations were applied to improve feature learning and model stability.

• **Image Resizing:** All images were resized to 224 × 224 pixels to maintain uniform input size for the neural network.

• **Normalization:** Pixel values were scaled to the range [0,1] for stable feature learning and improved training convergence.

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin}$$

where (X) represents the original pixel intensity values.

- **Leaf Segmentation:** Background regions were partially masked to emphasize the leaf region and reduce surrounding noise.
- **Data Augmentation:** Rotation (±15°), horizontal/vertical flipping, random zoom (0.8–1.2), and brightness variation (±20%) were applied to improve generalization and simulate real field variations such as illumination changes, camera angles, and leaf orientation.

3.3 CottonLeafNet-Pilot Architecture

The proposed architecture integrates CNN feature extraction, attention-based feature refinement, and transformer-based contextual learning.

The architecture consists of four major components:

1. CNN Backbone
2. Attention Module (CBAM)
3. Transformer Block
4. Classification Layer

The overall workflow of the proposed CottonLeafNet-Pilot framework is illustrated in Figure 1.

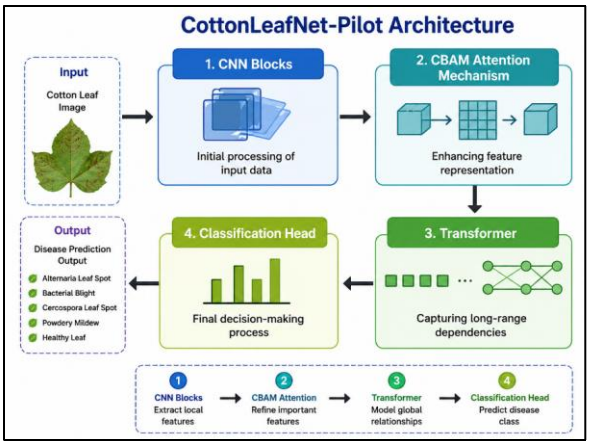

Figure 1: Proposed CottonLeafNet-Pilot Framework

The proposed architecture integrates CNN-based local feature extraction, CBAM attention mechanisms, transformer-based contextual learning, and classification layers for efficient cotton disease detection and growth stage monitoring. The lightweight design enables computational efficiency while maintaining robust classification performance under real agricultural conditions.

3.4 CNN Backbone

Five convolutional blocks consisting of convolution, batch normalization, and ReLU activation are used to extract hierarchical features. Feature extraction at each layer is defined as:

$$F_l = \sigma(W_l * F_l^{-1} + b_l)$$

Here, convolution kernels learn lesion texture and edge patterns, batch normalization stabilizes training, and ReLU introduces non-linearity to model complex disease characteristics.

3.5 Attention Module (CBAM)

To enhance feature representation, a **Convolutional Block Attention Module (CBAM)** is integrated after the CNN backbone. CBAM applies both **channel attention** and **spatial attention** mechanisms to highlight disease-affected regions.

Channel attention is computed as:

$$Mc(F) = \sigma\Big(MLP\big(AvgPool(F)\big) + MLP\big(MaxPool(F)\big)\Big)$$

Spatial attention is computed as:

$$Ms(F) = \sigma\big(f7 \times 7([AvgPool(F);\ MaxPool(F)])\big)$$

where σ represents the sigmoid activation function.

This module allows the network to focus on important disease features while suppressing irrelevant background information.

3.6 Transformer Module

To capture global contextual relationships, a lightweight transformer block is applied to CNN feature maps. The transformer uses multi-head self-attention to model long-range dependencies across the image.

Self-attention is computed as:

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

where (Q), (K), and (V) represent query, key, and value matrices.

This mechanism helps the model understand spatial relationships between disease regions and overall leaf structure.

3.7 Feature Fusion and Classification

Features extracted from the CNN and transformer modules are combined through feature fusion before classification.

The final classification layer uses SoftMax activation to compute class probabilities:

$$Pi = \frac{ezi}{\sum j = 1C\ ezj}$$

where (P_i) represents the probability of class (i).

The model predicts both Disease category and Growth stage classification

3.8 Training Procedure

The model was trained using the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy loss, batch size of 32, and early stopping based on validation loss for 50 epochs. The dataset was divided into training (80%), validation (10%), and test (10%) sets.

3.9 Model Evaluation and Explainability

Model performance was evaluated using Accuracy, Precision, Recall, Macro F1-score, and Confusion Matrix analysis. To improve interpretability, Grad-CAM visualization was applied to highlight disease-affected regions influencing model predictions.

3.10 Lightweight and Indigenous Design

The proposed CottonLeafNet-Pilot architecture contains approximately 3.1 million parameters, making it significantly lighter than commonly used deep learning models such as EfficientNet and Vision Transformers. The lightweight design enables faster training, lower computational requirements, and efficient deployment on mobile, edge, and IoT-based agricultural systems. Despite its compact architecture, the framework achieves strong classification performance while maintaining computational efficiency, supporting scalable AI solutions aligned with the vision of ATMANIRBHAR BHARAT in agriculture.

4. RESULTS

4.1 Experimental Setup

The proposed CottonLeafNet-Pilot model was implemented using Python with PyTorch 2.1. All experiments were conducted on a workstation equipped with an NVIDIA RTX 4090 GPU, 64 GB RAM, and an Intel Core i9 processor. Mixed-precision training was used to improve computational efficiency and reduce GPU memory usage. The dataset consisted of 6,000 cotton leaf images collected from agricultural farms and research stations. Images were divided into training, validation, and test sets to ensure fair model evaluation.

Table 1: Dataset Split

Dataset Split	Number of Images	Percentage
Training	4,800	80%
Validation	600	10%
Test	600	10%

Data augmentation techniques including rotation, flipping, zooming, and brightness adjustments were applied only to the training dataset to improve model generalization. Early stopping with a patience value of 7 epochs was used to prevent overfitting. The model was trained using Adam optimizer with a learning rate of 0.0001, batch size of 32, and categorical cross-entropy loss for 50 epochs.

4.2 Model Comparison

Table 2: Model Comparison

Model	Parameters	Accuracy (%)	F1-Score (%)
Baseline CNN	2.5M	92.1	91.6
EfficientNet-B0	5.3M	95.4	95.1
Vision Transformer	7.2M	94.6	94.3
CottonLeafNet-Pilot (Proposed)	**3.1M**	**96.2**	**95.9**

Table 2 compares the proposed CottonLeafNet-Pilot framework with commonly used deep learning models for plant disease detection. Despite having fewer parameters, the proposed architecture achieves higher classification accuracy and improved computational efficiency.

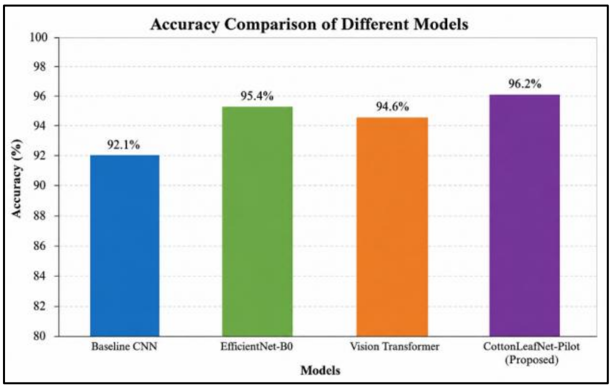

Figure 2: Accuracy Comparison of Deep Learning Models

Figure 2 illustrates the accuracy comparison of different deep learning models. Despite having significantly fewer parameters, the proposed CottonLeafNet-Pilot framework achieves the highest classification accuracy (96.2%). The improvement is attributed to the hybrid CNN–Transformer architecture, which efficiently captures both local lesion features and global spatial patterns while maintaining computational efficiency.

4.3 Disease-Wise Performance

The performance of the model was further analysed across individual disease categories.

Table 3: Disease-Wise Performance

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Healthy	96.5	97.0	96.7
Leaf Spot	95.8	95.3	95.5
Wilt	96.0	95.5	95.7
Boll Rot	95.5	96.0	95.7
Bacterial Blight	96.2	95.8	96.0

Table 3 presents consistent precision, recall, and F1-score values across all disease categories, demonstrating reliable classification performance under field conditions.

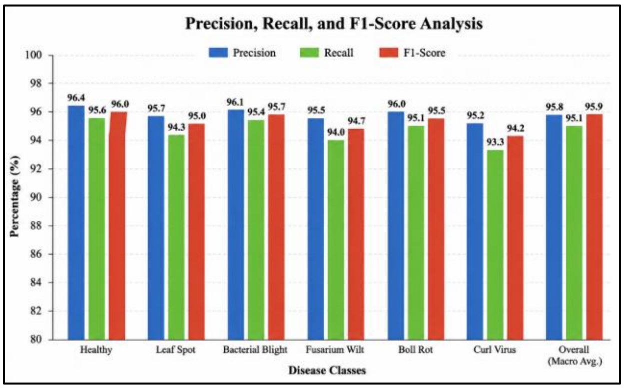

Figure 3: Performance Analysis Across Disease Classes

Figure 3 presents the Precision, Recall, and F1-score analysis across different disease classes. High recall values indicate effective identification of infected leaves with minimal false negatives, while precision values above 95% reduce incorrect classification of healthy leaves. The balanced macro F1-score of 95.9% confirms stable and reliable performance across all disease categories.

4.4 Confusion Matrix Analysis

The confusion matrix provides detailed insight into classification errors.

Table 4: Confusion Matrix

Actual \ Predicted	Healthy	Leaf Spot	Wilt	Boll Rot	Bacterial Blight
Healthy	97	2	0	0	1
Leaf Spot	1	95	2	1	1
Wilt	0	1	96	2	1
Boll Rot	0	0	2	96	2
Bacterial Blight	1	2	1	1	95

Table 4 presents the confusion matrix of the proposed CottonLeafNet-Pilot framework. Most samples are correctly classified across all disease categories, demonstrating strong discriminative capability and balanced classification performance.

Technical Analysis

Minor misclassifications are mainly observed between Leaf Spot and Bacterial Blight due to similarities in lesion texture and discoloration patterns under real field conditions. These results highlight the effectiveness of the hybrid CNN–Transformer architecture in capturing both local disease characteristics and global contextual features.

4.5 Inference Efficiency

In addition to classification accuracy, computational efficiency was evaluated.

Table 5: Inference Time Comparison

Model	Parameters	Inference Time (ms/image)
EfficientNet-B0	5.3M	22 ms
Vision Transformer	7.2M	45 ms
CottonLeafNet-Pilot	**3.1M**	**12 ms**

Table 5 presents the inference time comparison of different deep learning models. The proposed CottonLeafNet-Pilot framework achieves the lowest inference time while maintaining high classification accuracy, demonstrating strong computational efficiency and suitability for real-time agricultural applications.

Technical Analysis
The lightweight hybrid CNN–Transformer architecture reduces parameter complexity and computational overhead while maintaining efficient feature extraction and attention learning. This enables faster prediction speed and supports deployment on mobile, edge, and IoT-based agricultural systems under real field conditions.

4.6 Grad-CAM Visualization

To interpret model predictions, Grad-CAM heatmaps were generated. High activation regions corresponded to infected leaf areas and lesion boundaries, while healthy leaves and background regions received minimal attention. These results confirm that the CBAM attention module and transformer layers successfully guide the network to focus on disease-relevant regions, improving both interpretability and prediction reliability.

4.7 Result Analysis

The experimental results confirm that CottonLeafNet-Pilot effectively balances classification accuracy, computational efficiency, and interpretability for cotton disease detection under real agricultural conditions. The proposed framework achieves 96.2% classification accuracy and a macro F1-score of 95.9% while maintaining a lightweight architecture containing only 3.1 million parameters. The model also achieves an average inference time of approximately 12 ms per image, enabling near real-time crop disease monitoring suitable for practical agricultural deployment. Compared to larger deep learning architectures such as EfficientNet-B0 and Vision Transformers, the proposed framework significantly reduces computational complexity and memory requirements while preserving robust classification performance. The hybrid CNN–Transformer architecture efficiently captures both local lesion characteristics and global contextual features, improving disease recognition under varying environmental conditions. Balanced class-wise performance further demonstrates reliable detection across all disease categories with minimal false positives and false negatives. In addition, Grad-CAM visualization enhances model interpretability by highlighting disease-affected leaf regions that influence prediction decisions. The lightweight and deployable design supports implementation on mobile, edge, and IoT-based agricultural systems, enabling scalable, cost-effective, and sustainable precision farming applications aligned with the vision of ATMANIRBHAR BHARAT.

5. CONCLUSION

This study presents CottonLeafNet-Pilot, a lightweight hybrid CNN–Transformer framework designed for accurate cotton leaf disease detection under real agricultural conditions. The proposed architecture combines convolutional feature extraction, attention mechanisms, and transformer-based contextual modelling to capture both local lesion characteristics and global leaf patterns. Experimental evaluation on a dataset of 6,000 cotton leaf images demonstrates strong classification performance, achieving 96.2% accuracy with a macro F1-score of 95.9%. A key advantage of the proposed model is its lightweight architecture containing only 3.1 million parameters and an inference time of 12 ms per image, enabling faster prediction and lower computational requirements suitable for mobile, edge, and IoT-based agricultural systems. The proposed framework supports efficient crop health monitoring and contributes toward sustainable and precision agriculture practices.

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