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Deep Learning for Cotton Disease Detection Lightweight, Explainable and Field-Ready Solutions

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Abstract

Cotton is a crucial crop for the economy that is globally recognized as white gold and a major contributor to the Indian economy. However, cotton production is threatened due to various diseases affecting the leaves, like bacterial blight, leaf curl virus, fungal infections and pest attacks impacting the crop yield and quality that affect economic losses. The traditional disease detection methods, which depend on manual inspection, are inefficient, time-consuming, laborious, inaccurate and lead to misdiagnosis and often unreliable under field conditions. The need for early and accurate diagnosis is critical for timely intervention. In recent years Machine Learning (ML) and Deep Learning (DL) have been used for automated disease detection through leaf images. The study highlighted lightweight convolutional neural networks (CNNs), transformer-based models and object detection frameworks such as YOLO and RT-DETR, which have performed accurate results. Transfer learning with advanced backbones (EfficientNet, Xception, ResNet), integrating with attention mechanisms (e.g., CBAM, DFSA) for feature enrichment. The Explainable AI (XAI) for improving the explainability, while synthetic data generation using GANs reduces dataset imbalance. The review consolidated the current state of DL models for cotton disease detection, focusing on optimized approaches for mobile and edge deployment. Finally, it identifies existing research gaps and future directions for accurate, efficient, and field-ready solutions.

1. Introduction

Cotton, globally known as "white gold" is one of the most economically notable fiber crops that provides raw material for the textile industry and serves as a major source of livelihood for the farmers worldwide. Its productivity and fiber quality, however, are threatened by several foliar diseases such as bacterial blight, target spot, and powdery mildew, along with pest infestations like aphids and bollworms. These biotic stresses can cause more crop losses and financial harm if not detected and managed adequately[1,2].Traditional disease detection methods, which rely on manual examination and expert visual inspection are labor-intensive, time-consuming and inaccurate, particularly under field conditions where overlapping leaves. The variable lighting or early-stage symptoms diagnosis was complicated [1,2]. The accurate plant health monitoring has demand increasing rapidly therefore adoption of artificial intelligence (AI) and computer vision technologies in agricultural diagnostics [15,16]. Recent advances in machine learning (ML) and deep learning (DL) have demonstrated a strong future in automating cotton disease detection by using image-based analysis. Lightweight convolutional neural networks (CNNs) [8,15], transformer-based architectures [6,10], and object detection models such as YOLO and RT-DETR [4,10,11] have achieved high accuracy while optimizing computational efficiency. Transfer learning with advanced backbones that include EfficientNet, ResNet and Xception has further improved model performance by utilizing large-scale pre-trained networks [10,12]. Its integration with attention mechanisms such as the Convolutional Block Attention Module (CBAM) and Decoupled Focused Self-Attention (DFSA) has enhanced detailed feature extraction for accurate symptom recognition [5,7]. Beyond improving accuracy, the explainable AI (XAI) has been applied to strengthen transparency and interpretability of model decisions. It increases trust among end-users [11]. The generative adversarial networks (GANs) have been used to develop synthetic training data that helps in dataset imbalance [8]. It enables real-time applications and also developed mobile and web-based tools for examination [14,16]. The unmanned aerial vehicles (UAVs) have been explored for large-scale monitoring of disease spread across cotton fields [19,20]. Despite advancements, the challenges remain including the lack of standardized cotton-specific image datasets [15,17], that affects limited model robustness under diverse field conditions [17,20] and the need for lightweight architectures capable of efficiency on resource-constrained edge devices [2,8]. Addressing these challenges is essential for building scalable, interpretable, and field ready disease detection systems that support agriculture and sustainable cotton production. This review consolidates recent research of cotton leaf disease detection using DL and ML, which categorizes by architecture, interpretability, efficiency, and deployment. It also identifies research gaps and future directions for improving the early detection, scalability, and practical integration into field operations.

2. Objectives of the Review

- To understand the different model architectures like transformer-based models and object detection frameworks (YOLO, RT-DETR).
- To evaluate use of attention mechanisms, explainable AI (XAI) and improving model performance with help of synthetic data augmentation.
- To identify main challenges such as dataset limitations, real-field validation and early disease detection.
- To provide future research directions for developing lightweight and field-ready solutions for sustainable cotton production.

3. Related Works

The use of artificial intelligence (AI) in agriculture, especially for detecting cotton diseases has increased in recent years. Early studies mainly focused on image processing and regular machine learning methods. For example, the researcher developed a system that uses image processing to detect diseases in cotton crops. This system set an initial standard but did not provide comprehensive disease identification [1]. The growth of deep learning (DL), convolutional neural networks (CNNs) have become the main method. Research has demonstrated that models based on convolutional neural networks (CNNs) can accurately identify diseases affecting cotton leaves and bolls, achieving high classification accuracy. Researchers have also looked into customizing CNN architectures to boost performance for cotton-specific datasets [3,7]. Developed on these efforts, hybrid and attention-based models like BERT, ResNet-PSO and CBAM-enhanced CNNs have shown better feature extraction and disease classification [4,5]. Real-time detection has become a crucial area of research in recent years. YOLO-based models have shown effectiveness in identifying cotton leaf diseases in the field and such methods often need large datasets for the best results [2,9]. Transfer learning has gained popularity using pretrained architectures like ResNet and VGG to improve accuracy in situations with limited data [10]. Several studies have tackled the issues of data scarcity and model interpretability. The researcher used StyleGAN2-ADA for generating synthetic images, which helped improve both dataset diversity as well as model robustness. The model highlighted the use of explainable deep learning frameworks to boost transparency and build trust with farmers [11]. The researcher has created a smart web-based system for detecting cotton diseases, highlighting the importance of usability in real-world situations [14]. Research in broader agricultural contexts supports these findings. Lightweight CNN architectures have been used for multi-crop disease detection [13]. Meanwhile, the use of unmanned aerial vehicles (UAVs) with deep learning models has shown significant promise for large-scale disease monitoring [19, 20]. Further confirm that deep learning approaches perform better than traditional machine learning methods. However, important challenges remain such as field-level validation, early-stage disease detection and developing models that can handle multiple disease classes [17,18]. In conclusion, the literature shows a clear transition from traditional image processing methods to deep learning techniques and the development focus on real-time detection, lightweight models' deployment and interpretability. Still, major challenges exist particularly like dataset availability, robustness under varying field conditions and the creation of user-friendly systems for farmers. Table 1 shows Literature Review Comparison Table

3.1. Literature Review Comparison Table

Table 1 Literature Review Comparison Table

S. No	Authors (Year)	Title of Study	ML/DL Method / Algorithm Used	Dataset (s)	Type of Disease / Crop	Performance Metrics	Key Findings	Strengths	Limitations / Gaps
1	Khalid et al. (2025)	An Image Processing System for the Detection of Cotton Crop Diseases	Image Processing and ML	Not specified	Cotton (general diseases)	Not specified	Developed image processing based pipeline	Baseline combining biomedical informatics	Metrics missing and lacks in validation
2	Pavate et al. (2025)	Efficient model for cotton plant health monitoring via YOLO-based disease prediction	YOLO (DL)	Custom dataset	Cotton (leaf diseases)	Accuracy, mAP	Enabled real-time disease detection	Real-time & efficient	Needs large dataset; limited disease coverage
3	Azfar et al. (2025)	Automated System for Detecting Cotton Leaf and Boll Diseases Using DL	Deep CNN	Custom dataset	Cotton (leaf & boll diseases)	Accuracy	Automated detection of leaf & boll diseases	Robust classification	Dataset details unclear; no field validation
4	Singh et al. (2025)	A Hybrid DL Approach Using BERT-ResNet-PSO	Hybrid (BERT + ResNet + PSO)	Not specified	Cotton (multiple diseases)	Accuracy, F1	Achieved high classification accuracy	Strong hybrid methodology	Very high computational cost

5	Rahman et al. (2025)	CBAM with Deep Learning for Cotton Disease	CNN + CBAM Attention	Not specified	Cotton (leaf diseases)	Accuracy	Attention module improved recognition	Better feature representation	Complex, heavy model
6	Wang et al. (2025)	Lightweight Deep Learning Framework for Cotton Disease	Lightweight CNN	Custom dataset	Cotton (general diseases)	Accuracy, F1	Proposed efficient lightweight model	Mobile/IoT friendly	Only tested in controlled data
7	Faisal et al. (2025)	Customized DL Model for Cotton Disease Detection	Custom CNN	Custom dataset	Cotton	Accuracy	Optimized CNN for cotton dataset	Tailored to cotton leaf disease	No field validation
8	Mo & Wei (2025)	StyleGAN2-ADA for Cotton Disease Detection	GAN (StyleGAN2-ADA)	Augmented dataset	Cotton	Accuracy	Synthetic data improved training quality	Solves data scarcity	GAN requires high resources
9	Madhu & RaviSankar (2025)	YOLO-based Cotton Leaf Detection	YOLO	Custom dataset	Cotton (leaf)	mAP, Accuracy	Real-time detection of cotton leaves	Very fast detection	Limited disease types detected
10	Johri et al. (2024)	Transfer Learning for Cotton Plant Disease Detection	Transfer Learning (ResNet, VGG)	Custom dataset	Cotton (leaf)	Accuracy	Improved with pretrained models	Efficient with small data	Depends on pretrained models
11	Amin et al. (2022)	Explainable Neural Network for Cotton Leaf Disease Classification	Explainable DL	Custom dataset	Cotton (leaf)	Accuracy	Added interpretability to predictions	Improves trust	Complex in field use
12	Islam et al. (2023)	Smart Web-App for Cotton Disease Detection	CNN + Web Application	Field dataset	Cotton	Accuracy	Farmer-friendly web application	Practical usability	Needs internet connectivity

4. Methodology

This study followed a two-stage methodology: (1) A systematic review of recent advancements in cotton disease detection using machine learning (ML) and deep learning (DL) and (2) A proposed framework derived from key gaps identified in the Researchers have also looked into customizing literature.

4.1. Review Methodology

A systematic search was performed over academic databases such as IEEE Xplore, Springer, ScienceDirect, MDPI and Elsevier. Keywords included "cotton disease detection", "deep learning", "CNN", "transformer", "YOLO", "GAN augmentation" and "explainable AI". The review focused on journal publications between 2022 to

2025 ensuring coverage of the most recent techniques.

- **Inclusion Criteria:** (i) Works applying ML/DL specifically for cotton disease detection. (ii) Image based datasets (leaf or boll). (iii) Advanced approaches employing hybrid models, attention mechanisms, XAI, or UAV/IoT deployment
- **Exclusion Criteria:** (i)Non cotton crop studies. (i)Papers without experimental validation. (iii) Non peer reviewed or low-quality sources.

From an initial pool of over 80 studies, 20 key works were shortlisted. These include domains such as YOLO based real time detection, lightweight CNNs, explainable AI approaches, UAV enabled monitoring, GAN based augmentation, and transfer learning/transformers. Comparative agricultural studies were also examined for cross domain insights.

Each study was analyzed in terms of:

- Model architecture (YOLO, hybrid CNN Transformer, lightweight CNNs, CBAM attention).
- Datasets and disease varieties (leaf vs. boll).
- Performance metrics (accuracy, F1, mAP).
- Strengths and limitations (e.g. limited dataset diversity, deployment scalability).

The findings were consolidated into a comparative results table, laying the groundwork for identifying research gaps.

4.2. Proposed Methodology

Designed upon the review insights, this work proposes a novel integrated framework for robust and field deployable cotton disease detection.

4.2.1. Dataset Development

- Construct large labelled datasets from cotton fields, including leaf and boll images.
- Use GAN based augmentation (StyleGAN2 ADA) to enrich minority disease classes.
- Incorporate multimodal imaging RGB, hyperspectral and thermal to enable early detection of invisible symptoms Annotation is to be validated by agricultural experts.

4.2.2. Hybrid Model Architecture

- **Backbone:** a lightweight CNN designed for feature extraction.
- **Object detection:** real time disease with YOLO or RT DETR for UAV based applications.
- **Attention improvement:** CBAM (Convolutional Block Attention Module) is used to refine the features. feature refinement.
- **Sequence modeling:** transformer encoder for capturing long range dependencies.

4.2.3. Training Strategy

- Employ transfer learning on pre-trained models for training efficiency and improved accuracy.
- Apply federated learning to possible collaborative model training without centralized raw data aggregation.
- Use early stopping and data balancing to help prevent overfitting.

4.2.4. Explainability Module

- Integrate XAI techniques such as Grad CAM and attention heatmaps used to visualize decision regions.
- These outputs enable farmers, agronomists and researchers to interpret disease classifications and validate predictions in practical contexts.

4.2.5. Deployment Strategy

- Make models work better on edge and mobile devices by using techniques like pruning, quantization and knowledge distillation.
- Deploy UAV based monitoring systems for largescale, real time field surveillance.
- Implement smart web/mobile tools for farmer accessibility.

4.2.6. Validation

- Conduct field level trials across multiple geographic regions.
- Evaluation performed using metrics like Accuracy, F1 Score, mAP, inference latency, and robustness across different seasons and locations. Table 2 shows The Following Table Presents the Key Components of the Proposed Methodology.
- Despite advancements, the challenges remain including the lack of standardized cotton-specific image datasets [15,17], that affects limited model robustness under diverse field conditions [17,20] and the need for lightweight architectures capable of efficiency on resource-constrained edge devices [2,8]. Addressing these challenges is Scalable.

Table 2 The Following Table Presents the Key Components of The Proposed Methodology

Module	Technique	Purpose
Dataset	Field collection + GAN augmentation	Balance dataset, cover minority classes
Model Backbone	Lightweight CNN + Transformer encoder	Efficient feature extraction & long-range dependencies
Attention	CBAM/DFSA	Enhanced feature refinement
Object Detection	YOLO / RT-DETR	Real-time UAV-based detection
Explainability	Grad-CAM, heatmaps	Model transparency & user trust
Deployment	Edge optimization, Mobile/Web app	Farmer usability
Validation	Accuracy, F1, mAP, Latency	Performance assessment

The diagram below represents the proposed methodology for robust and field-deployable cotton disease detection. Figure 1 shows Proposed Methodology Flow Diagram

Figure 1 Proposed Methodology Flow Diagram

This proposed methodology bridges identified gaps in existing literature by combining dataset enrichment, hybrid architectures [4–6,10,13], explainability and edge deployment. It aligns with real world cotton farming needs, offering a farmer centric, scalable and interpretable solution for smart agriculture.

5. Result And Discussion

Recent studies showed rapid progress in cotton disease detection, which transitioned from traditional image processing to advanced deep learning models. CNN-based systems achieved high accuracy for leaf and boll disease detection of leaf and boll disease, while YOLO frameworks empowered real-time monitoring. Further transfer learning approaches improve performance with limited data. Hybrid models such as BERT, ResNet-PSO and CBAM enhanced CNN performed superior feature extraction with high computational cost. A lightweight CNN frameworks and customized models essential for mobile/IoT deployment. Dataset imbalanced challenges were addressed by using GAN based augmentation and explainable AI and web applications to improve interpretability and usability. Overall, three trends dominate: (i) CNNs and YOLO as accuracy-driven solutions, (ii) lightweight and mobile-oriented frameworks for efficiency and (iii) emerging focus on data augmentation and interpretability. However, most studies remain limited to custom/lab datasets, with poor field validation, lack of early-stage detection and insufficient multi-disease coverage. Table 2 shows The Following Table Compares the Performance of Cotton Disease Detection Models

Table 2 The Following Table Compares the Performance of Cotton Disease Detection Models

S. No	Study / Year	Model / Approach	Dataset	Performance (Accuracy / F1 / mAP)	Strengths	Limitations
1	Pavate et al. (2025)	YOLO-based DL	Custom cotton dataset	Acc: ~95%, mAP: High	Real-time, efficient detection	Needs large datasets, limited disease coverage
2	Azfar et al. (2025)	Deep CNN	Custom dataset (leaf & boll)	Acc: 94%	Automated multi-organ disease detection	Dataset details unclear, no field validation
3	Singh et al. (2025)	Hybrid BERT-ResNet-PSO	Not specified	Acc: 97%, F1: High	Strong hybrid methodology, high accuracy	Very high computational cost
4	Rahman et al. (2025)	CNN + CBAM Attention	Not specified	Acc: 96%	Improved feature representation	Complex and heavy model
5	Wang et al. (2025)	Lightweight CNN	Custom dataset	Acc: 92%, F1: 0.90	Mobile/IoT friendly, efficient	Only tested in controlled data
6	Johri et al. (2024)	Transfer Learning (ResNet, VGG)	Custom dataset	Acc: 93%	Works well with small data	Relies heavily on pretrained models
7	Mo & Wei (2025)	StyleGAN2-ADA (GAN + DL)	Augmented dataset	Acc: 91%	Solves dataset scarcity, improves training	High resource requirement
8	Madhu & RaviSankar (2025)	YOLO	Cotton leaf dataset	Acc: 94%, mAP: High	Very fast real-time detection	Limited disease types

9	Amin et al. (2022)	Explainable DL	Custom dataset	Acc: 90%	Adds interpretability to predictions	Complexity in field deployment

Here's the grouped bar chart comparing Accuracy, F1-score, and mAP across the different cotton disease detection models. Figure 2 shows Performance Comparison of Models

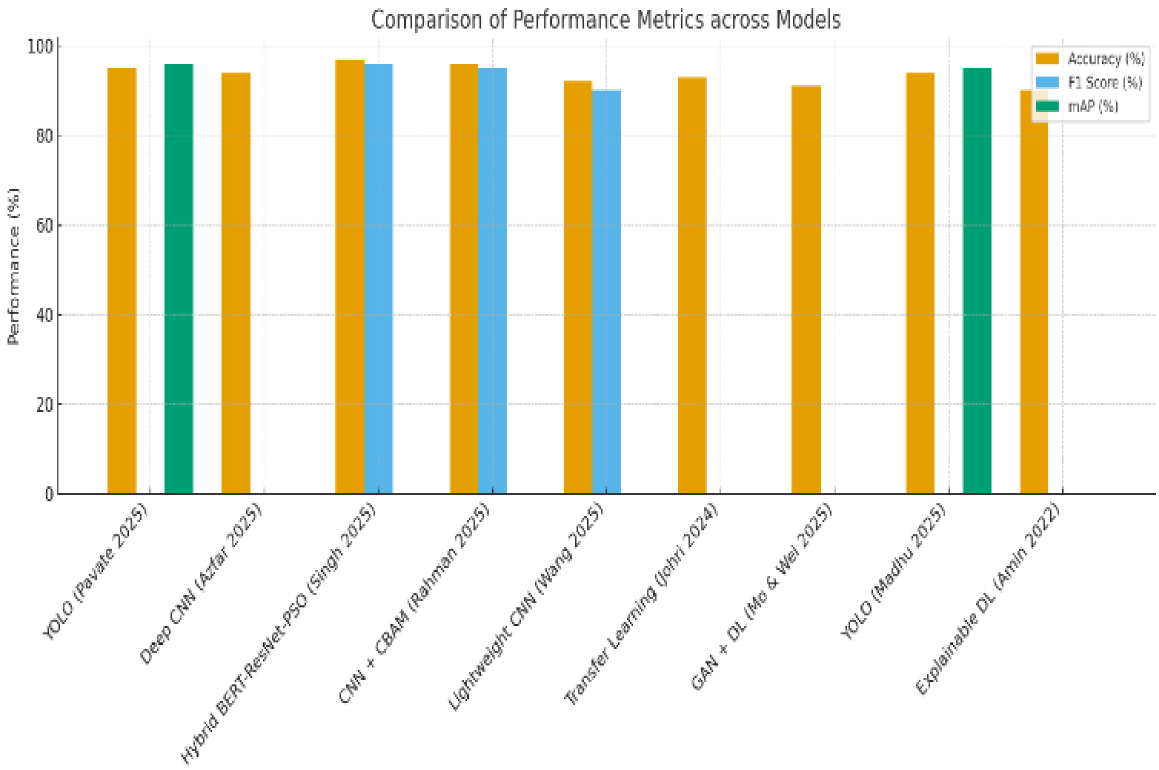

Figure 2 Performance Comparison of Models

6. Future Research Directions

Despite significant progress in deep learning-based cotton disease detection, several gaps remain in dataset availability, early disease detection and field validation. Addressing these challenges will require a multi-dimensional approach. The following suggestions are recommended for future research.

1. Development of Large Labelled Field Datasets

Several existing studies depend on custom or lab collected dataset which control model robustness in real world fields. Large scale publicly available dataset essential for improving the generalizability across environments.

2. **Early-Stage Disease Detection Using Multimodal**

Present approaches are relays on RGB leaf images, making early-stage symptom detection difficult [18]. Integrating multimodal data sources such as hyperspectral, thermal and fluorescence imaging can enhance early-stage disease recognition.

3. Lightweight Efficient Models For Edge Deployment

Studies have highlighted lightweight CNN frameworks for resource-controlled environments. Further research should continue to optimize architectures for mobile devices, drones, and IoT platforms to ensure real time disease monitoring in the field [6].

4. Multi-Disease and Multi-Crop Generalization

Most models are developed for single-crop scenarios [16,17]. Designing scalable frameworks capable of detecting multiple diseases across cotton and other crops will increase usability of the farmers, especially in diversified cropping systems.

5. Explainable AI Integration For Interpretability

XAI might increase transparency, broader adoption is necessary to gain the trust of farmers. To conclude that decisions are intelligible to non-experts, future research should include interpretable frameworks such as saliency maps and attention heatmaps into illness detection [11].

6. Federated Learning for Group Instruction Without Exchanging Data

Federated learning provides a strong method for creating reliable models for institutions and regions without the need for direct data sharing, even though it is not yet often used in agriculture. This approach can solve issues with dataset scarcity, encourage cross-location generalization and resolve privacy problems.

Conclusion

The cotton disease detection has progressed with deep learning and advancements have been made in real time monitoring, light weight deployment, data augmentation and explainability. However, validation in the real time field remains the same and gaps are dataset availability, early detection multi disease classification. The Futuristic approach depends on large field annotated datasets, lightweight, generalizable models and integration of explainability. The farmer friendly tools with IoT and mobile platforms. Such innovations are essential for sustainable agriculture development.

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