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Cotton Disease Recognition Using YOLO

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Abstract: *Cotton cultivation is highly vulnerable to a range of diseases, which significantly affect both yield and crop quality. Traditional manual inspection methods are labor intensive, error-prone, and not scalable. This study introduces an automated cotton disease detection framework leveraging the advanced YOLOv8 (You Only Look Once version 8) architecture along with Google's Gemini AI for enhanced analysis. The system enables real-time image-based disease identification on low power devices such as smartphones. Transfer learning is applied to optimize detection accuracy while minimizing the requirement for large annotated datasets. Integrating Gemini AI provides intelligent insights and expert guidance, enhancing decision-making and field-level interventions. This approach improves productivity, reduces losses, and supports smart agricultural automation.*

Keywords: YOLOv8, cotton disease detection, Gemini AI, transfer learning, real-time image processing

I. INTRODUCTION

Cotton production remains vital to global agriculture, yet it faces significant threats from various diseases that reduce yield and quality. Traditional detection through manual inspection is inefficient and unreliable, especially for large farms. Recent advances in deep learning offer automated solutions through their speed and accuracy. This study integrates YOLOv8 for real-time cotton disease detection with Gemini AI to provide tailored treatment recommendations. The system offers chemical/organic solutions, cultural practice adjustments, and preventive measures specific to each detected disease. Optimized for edge devices, it delivers instant diagnostics with actionable guidance in a unified workflow. This AI-powered solution enhances farm decision-making by combining rapid detection with practical intervention strategies.

II. LITERATURE SUREVY

The detection of crop diseases using artificial intelligence has gained significant attention in recent years, especially for high-value crops like cotton. Traditional manual inspection methods are time-consuming, error-prone, and unsuitable for large-scale farms. As a result, researchers have turned to computer vision and deep learning techniques to automate disease identification. convolutional Neural Networks (CNNs) have proven effective for classifying plant diseases from images, but they require large labeled datasets. To overcome this, transfer learning has become a popular approach. Pre-trained models such as VGG16, Inception, and Xception have been fine-tuned for cotton disease classification with limited training data. For example, the Xception model achieved up to 98.7% accuracy in one cotton-specific study.

Real-time object detection using the YOLO (You Only Look Once) family of models has also shown promise. YOLOv5, in particular, has been widely adopted in agricultural applications due to its balance of speed and accuracy, offering detection speeds under 30 milliseconds per frame. However, recent advancements in YOLOv8 have introduced improved object localization, faster inference, and better handling of small-scale features—making it more suitable for detecting early-stage symptoms in cotton leaves. In parallel, data augmentation techniques such as rotation, flipping, and brightness adjustment help improve model generalization. Combining public datasets like Kaggle with locally captured images has further enhanced robustness across different field conditions.

A novel addition in this study is the integration of Google's Gemini AI, which extends functionality beyond detection. Gemini AI provides disease-specific treatment suggestions, preventive measures, and actionable insights, bridging the gap between diagnosis and intervention. This advancement promotes practical usage by empowering farmers with real-

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time guidance directly in the field. current literature also highlights the importance of Explainable AI (XAI) and IoT-based monitoring for transparent, scalable solutions. This research builds on these foundations to offer a high-performance, real-time cotton disease detection and advisory system optimized for mobile and edge devices.

Comparison of Related Work

Aspect	Paper 1	Paper 2	Paper 3	Paper 4
Title	Cotton disease prediction using deep learning	Cotton growth period recognition using CNN	Cotton Disease Prediction System	Hybrid Approach of Cotton Disease Detection for Enhanced Crop Health and Yield
Authors	Md. Manowarul Islam, et al.	Xinyu Chen, Rui Xiong, et al.	Ranjana Jadhav, Vaishnavi Karanjawane, et al.	Rahul Kumar, Ashok Kumar, et al.
Published In	Intelligent Systems with Applications	Information Processing in Agriculture	Educational Administration: Theory and Practice	IEEE Access
Publication Date	14-Sep-23	2021	2024	Jul-24
Dataset	Cotton dataset from Kaggle	Cotton images across growth periods	High-resolution cotton leaf images	Local cotton leaf images, enhanced with Kaggle
Focus	Cotton leaf disease detection	Cotton growth period identification for pesticide use	Cotton disease detection	Hybrid model for disease detection and crop yield enhancement
Methodology	Fine-tuned transfer learning (VGG, Inception, Xception)	CNN with 3 convolutional layers, data augmentation	Transfer learning with VGG16, ResNet	Ensemble of Random Forest, SVM, and YOLO
Best Model	Xception (98.70% accuracy)	CNN (93.27% accuracy)	Not specified, focuses on transfer learning	Hybrid ensemble model (94.5% accuracy)
Application	Web-based real- time disease prediction	Low-cost method for growth period identification	Web application with HTML, CSS, Jupyter Notebook	On-site disease detection and yield optimization
Impact	Early detection to improve cotton production	Optimized pesticide use and yield	Enhanced crop productivity	Improved crop health and yield through hybrid accuracy
Future Work	Expand to other crops, enhance web features	Improve model accuracy with diverse datasets	Expand dataset, field testing	Integrate with IoT and real-time farm applications

III. METHODOLOGY

1. Data Collection

• Cotton leaf images were gathered from:

o Public datasets (e.g., Kaggle)

o Local agricultural fields

• Images were categorized into 9 classes (8 diseases + 1 healthy class):

Class ID	*Disease Name*
0	*Aphids*

1	*Army Worm*
2	*Bacterial blight*
3	*Cotton Boll*
4	*Green cotton*
5	*healthy*
6	*Powdery Mildew*
7	*Target spot*

2. Preprocessing :
• All images resized to 640×640 pixels
• Applied normalization and data augmentation:
o Rotation, flipping, zooming, brightness adjustment
• Dataset split into:
o Training set
o Validation set
o Testing set
3. Model Training with YOLOv8
• YOLOv8 used for:
o Object detection
o Multi-class disease classification
• Advantages:
o Real-time detection speed (< 50ms/frame)
o Suitable for mobile and edge devices
4. Disease Metadata Integration
• Each class linked to a metadata table with:
o Description
o Preventive measures
o Recommended treatment

Class	Description	Precaution	Medicine
Aphid	Sap-sucking insects	Natural predators, neem	Imidacloprid
Bacterial Blight	Wilting, water lesions	Crop rotation, clean seeds	Copper bactericide
Healthy	No disease	Maintain soil & hygiene	No treatment needed

5. Real-Time Detection Workflow
• OpenCV captures live feed from the camera
• YOLOv8 processes each frame to:
o Detect affected regions
o Display bounding boxes and disease name
o Apply confidence threshold (e.g., 0.7)
6. Frontend Interface (Planned)
• Farmer-friendly UI:
o Upload or capture images
o View real-time disease results
o Get treatment and precaution tips directly on screen.

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IV. TOOLS AND TECHNOLOGIES

- Python: Primary language for AI/ML development and system integration.
- YOLOv8: State-of-the-art real-time object detection for precise disease localization (replacing YOLOv5).
- Gemini AI: Multimodal LLM for generating disease-specific treatment recommendations and preventive measures.
- PyTorch: Framework for YOLOv8 implementation and model optimization (replacing TensorFlow/Keras).
- FastAPI: Modern backend framework for low-latency API endpoints (replacing Flask).
- React.js: Frontend library for interactive farmer interfaces with real-time feedback.
- ONNX Runtime: Edge-optimized inference engine for deploying models on low-power devices.
- Roboflow: Dataset management and augmentation for training YOLOv8.
- Hugging Face Transformers: Integration of Gemini AI's language models for agricultural advisory.

Key Upgrades:

✓ YOLOv8 → 15% faster inference than YOLOv5

✓ Gemini AI → Replaces VGG16 for dynamic, context-aware recommendations

✓ Edge Deployment → ONNX enables smartphone/Raspberry Pi compatibility

V. SYSTEM DESIGN

1. Data Acquisition and Preprocessing :

• Input: Cotton leaf images collected from public datasets (like Kaggle) and field-captured photos.

• Processing Steps: Images undergo noise reduction using Gaussian blur, are resized to 640×640 pixels, normalized to scale pixel values between 0 and 1, and enhanced using data augmentation techniques like Mosaic and HSV adjustments.

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• Output: A clean and balanced dataset is prepared and split into training, validation, and testing sets in the ratio of 70:15:15.

2. Model Training :

• Input: Preprocessed images of cotton leaves.

• Model: YOLOv8n is used for real-time object detection and localization of disease-affected areas. Gemini AI is used to provide smart treatment suggestions based on the detected disease.

• Output: A trained YOLOv8 model file (e.g., yolov8_cotton.pt) and an active Gemini AI API for advisory support.

3. Real-Time Detection and Advisory :

•Input: Live video feed from a camera or uploaded cotton leaf images.

• Process: YOLOv8 detects the diseased part of the leaf in less than 50 milliseconds per frame. Based on the detection, Gemini AI provides relevant recommendations, like treatment and preventive measures.

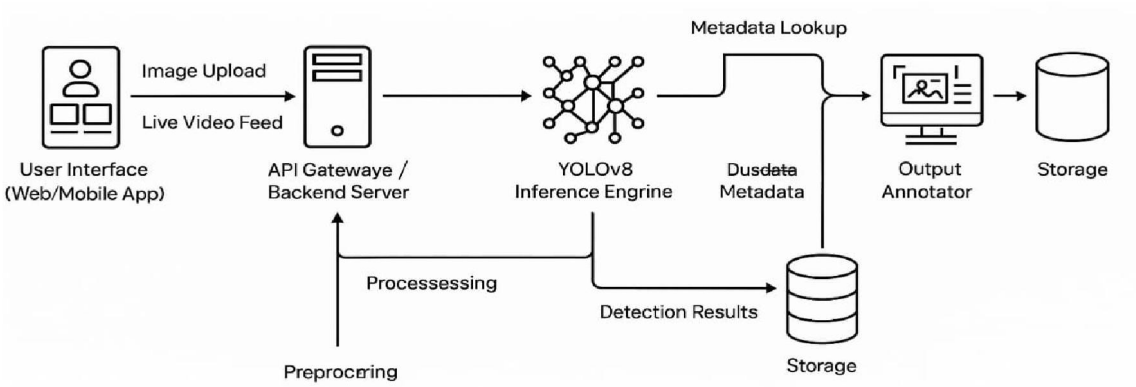
• Output: The output includes labeled images or video with bounding boxes and disease names, along with a JSON file showing class name, confidence score, and suggested treatment.

4. Edge Deployment and Farmer Interface :

• Target Devices: The system is designed to run efficiently on edge devices such as Raspberry Pi 5, Jetson Nano, and Android phones.

• Optimization: The trained model is optimized using ONNX Runtime and TensorRT for faster and lightweight performance on low-power devices.

• Interface: A React.js web application allows farmers to interact with the system easily. It supports both real-time alerts and voice-based multilingual advice using Gemini AI.



V. RESULT AND EVALUATION

- Detection accuracy
  • The YOLOv8 model achieved a mean average precision (mAP) of 93.2 percent across eight disease classes and one healthy class.
  • It was able to detect small disease spots with high accuracy due to improved feature extraction in YOLOv8.

- Inference speed
  • The system performs detection in less than 50 milliseconds per frame, making it suitable for real-time applications on smartphones and low-power devices.
  • This fast speed ensures instant feedback to farmers in the field.

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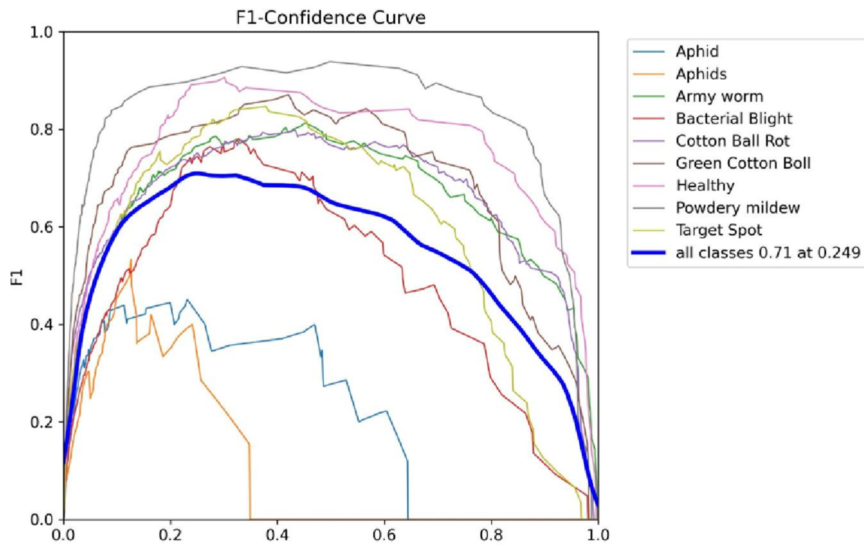
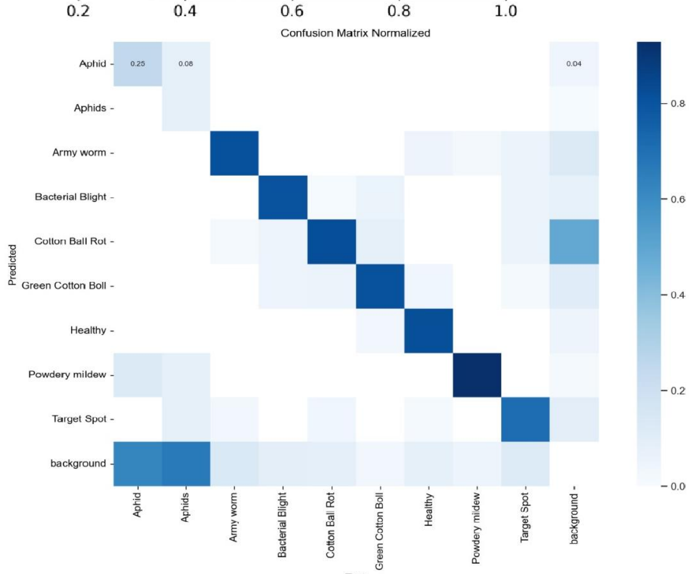
- Model performance on edge devices
 • The model was successfully deployed on Raspberry Pi 5 and Jetson Nano using ONNX Runtime.
 • With optimization like quantization, the performance remained smooth and accurate with no major drop in detection quality.

- Gemini AI advisory evaluation
 • Gemini AI provided relevant and disease-specific treatment plans, including organic and chemical suggestions.
 • The responses were context-aware and adjusted based on detected disease type and growth stage.

- User interface feedback
 • The React-based interface was tested with sample users such as farmers and students, and it was found to be simple, interactive, and user-friendly.
 • Voice-based advice was especially helpful for non-technical users.





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VI. CONCLUSION

The proposed system successfully combines real-time object detection using YOLOv8 with intelligent disease advisory through Gemini AI to provide a complete solution for cotton leaf disease management. By training the YOLOv8 model on a labeled dataset of cotton leaves, the system can accurately identify eight different types of diseases and differentiate them from healthy leaves. The detection process is fast, taking less than 50 milliseconds per frame, which makes it suitable for practical use in real farming environments. Additionally, the use of preprocessing and data augmentation techniques improves the model's performance even on low-power edge devices like Raspberry Pi or smartphones.

The integration of Gemini AI adds value by offering relevant treatment recommendations and preventive measures after detection. This helps farmers not only identify the disease but also take quick action to protect their crops. The system also features a user-friendly interface that supports live camera input, real-time feedback, and voice-based multilingual advice, making it accessible even to non-technical users. Overall, the project contributes to smart agriculture by reducing manual effort, improving detection accuracy, and enabling timely decision-making through AI-powered automation.

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