REAL-TIME COTTON LEAF DISEASE DETECTION AND PESTICIDE RECOMMENDATION USING DEEP LEARNING AND CONVERSATIONAL AI

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ABSTRACT

The increasing susceptibility of cotton crops to various diseases significantly affects agricultural productivity, particularly in regions where cotton is a major commercial crop. This project presents a **real-time cotton leaf disease detection and pesticide recommendation system** that integrates deep learning and conversational AI to support farmers in early diagnosis and effective decision-making. The proposed system utilizes a two-stage approach, where a YOLO-based model detects infected regions in cotton leaf images, followed by an EfficientNet-based classifier that identifies specific disease categories with high accuracy.

In addition to disease classification, the system incorporates confidence-based decision logic to handle uncertain predictions and enhance reliability in real-world conditions. A curated knowledge base provides appropriate pesticide recommendations, including dosage, application guidelines, and safety measures. Furthermore, a multilingual chatbot interface enables farmers to interact with the system and receive context-aware advisory support in an accessible manner.

The solution is designed for deployment on both cloud and edge devices, ensuring real-time performance with minimal resource requirements. By combining computer vision, deep learning, and interactive AI, the proposed system offers a comprehensive and user-friendly platform for crop health monitoring, ultimately improving disease management and crop yield optimization.

Keywords

Cotton Leaf Disease Detection, Deep Learning, Computer Vision, YOLOv4, EfficientNetB4, Pesticide Recommendation System, Precision Agriculture, Image Classification, Real-Time Monitoring, Conversational AI, Chatbot Interface, Crop Health Management

I. INTRODUCTION

Cotton is one of the most important commercial crops globally, playing a vital role in the agricultural economy, particularly in countries like India. However, cotton production is highly vulnerable to various leaf diseases and pest infestations, which can significantly reduce yield, increase pesticide usage, and ultimately affect farmers' income. Traditional disease detection methods largely depend on manual inspection and expert consultation, which are time-consuming, subjective, and often unavailable in remote farming regions. These limitations highlight the need for an automated, accurate, and real-time solution for crop health monitoring.

Recent advancements in **deep learning** and **computer vision** have enabled the development of intelligent systems capable of analyzing plant images and identifying diseases with high precision. In this context, the proposed system introduces a real-time cotton leaf disease detection framework that integrates detection, classification, and recommendation into a unified pipeline. The system employs a YOLO-based model to detect infected regions in leaf images, followed by an EfficientNet-based classifier to categorize diseases such as Aphids, Armyworm, Bacterial Blight, Powdery Mildew, Target Spot, and Healthy conditions.

Beyond simple disease identification, the system incorporates a **confidence-aware decision mechanism** to improve reliability by distinguishing between confident, uncertain, and suspect predictions. This reduces the risk of incorrect recommendations in ambiguous cases. Furthermore, the system connects the predicted disease to a structured treatment knowledge base, providing actionable insights such as pesticide selection, dosage guidelines, and safety precautions.

To enhance usability, a conversational AI-based chatbot interface is integrated into the system, allowing farmers to interact with the platform and receive context-aware guidance in their preferred language. The complete solution is implemented as a full-stack application with support for both cloud-based and edge deployment, enabling real-time analysis even in resource-constrained environments.By combining deep learning, computer vision, and conversational AI, this work aims to provide an accessible, scalable, and farmer-friendly decision support system for early disease detection and effective crop management.

II. LITERATURE REVIEW

Recent advancements in artificial intelligence and deep learning have significantly improved plant disease detection systems, particularly in agricultural applications. Several studies have explored different machine learning and deep learning approaches to enhance the accuracy, speed, and usability of disease diagnosis systems.

A comprehensive analytical review of YOLO-based object detection models highlighted the evolution from YOLOv1 to YOLOv8, emphasizing improvements in real-time detection speed and accuracy. The study concluded that modern YOLO variants provide an effective balance between performance and computational efficiency, making them suitable for real-time agricultural applications such as leaf disease detection.

In another study, a Random Forest-based model was applied for crop yield prediction using climatic datasets, achieving approximately 87% accuracy. Although focused on yield prediction rather than disease detection, this work demonstrated the importance of integrating machine learning models into user-friendly systems for practical agricultural decision support.

Deep learning approaches have also been successfully applied to cotton-specific disease detection. A convolutional neural network (CNN) trained on a self-collected dataset of cotton leaf images achieved nearly 99% accuracy in classifying disease severity levels. This study confirms the effectiveness of deep learning models in handling crop-specific datasets and highlights the importance of domain-specific data for improved performance.

Comparative research on traditional and modern plant disease management techniques revealed that conventional methods such as manual inspection and chemical control are often slow and less efficient. In contrast, modern diagnostic approaches, including molecular and AI-based techniques, provide faster and more accurate results, supporting sustainable agricultural practices.

Object detection and segmentation techniques have also been explored in agricultural contexts. A study using Faster R-CNN and Mask R-CNN for tomato disease detection demonstrated very high accuracy (mAP of 99.64%) by combining disease classification with infected region localization. This reinforces the effectiveness of multi-stage pipelines that integrate detection and classification, similar to the approach used in this project.

Another work developed a deep learning-based system for cotton leaf disease and pest diagnosis using CNN models trained on labeled datasets. The system achieved an accuracy of 96.4%, showing strong potential for real-world agricultural deployment.

The introduction of EfficientNet architectures further improved classification performance by optimizing model scaling across depth, width, and resolution. EfficientNet models have demonstrated high accuracy with reduced computational cost, making them suitable for deployment in resource-constrained environments such as mobile or edge devices.

Additionally, transfer learning techniques using architectures like EfficientNet and VGG16 have been applied to plant disease classification tasks. Studies have reported accuracy levels above 97%, confirming that pre-trained deep learning models can significantly enhance classification performance when applied to agricultural datasets.

III. METHODOLOGY

The proposed system follows a **multi-stage deep learning pipeline** that integrates data preprocessing, disease detection, classification, recommendation, and user interaction into a unified framework for real-time cotton leaf disease diagnosis.

1. Data Collection and Preprocessing

The initial stage involves collecting cotton leaf images across six classes: Aphids, Armyworm, Bacterial Blight, Healthy, Powdery Mildew, and Target Spot. The dataset undergoes preprocessing steps such as image cleaning, resizing, normalization, and augmentation to improve model generalization. Augmentation techniques including rotation, flipping, brightness adjustment, and zoom transformations are applied to handle variability in real-world conditions. The dataset is then divided into training, validation, and testing sets to ensure robust model evaluation.

2. Disease Region Detection using YOLO

A YOLO-based object detection model is employed to identify relevant leaf regions and infected areas from input images. The model processes images captured through a camera or uploaded by the user and generates bounding boxes around potential disease regions. Post-processing techniques such as filtering oversized or redundant detections and removing overlapping boxes are applied to improve detection quality. In cases where no valid region is detected, the system triggers a fallback mechanism to perform full-image classification.

3. Disease Classification using EfficientNet

The detected regions are passed to an EfficientNet-based classifier to identify the specific disease category. The input images are resized to a standard resolution (224×224), normalized, and fed into the trained model. The classifier outputs probability scores for each of the six disease classes. EfficientNet is chosen due to its high accuracy and computational efficiency, making it suitable for both cloud and edge deployment.

4. Confidence-Based Decision Logic

To enhance reliability, a confidence-aware decision mechanism is implemented. Predictions with low confidence or minimal difference between top class probabilities are labeled as *uncertain*, while moderate-confidence disease predictions are marked as *suspect*. Only high-confidence predictions are treated as reliable outputs. This approach reduces the risk of incorrect recommendations and improves practical usability in field conditions.

5. Pesticide Recommendation System

Once the disease is identified, the system maps the prediction to a predefined treatment database. It provides actionable recommendations, including suitable pesticides, dosage levels, application frequency, and safety precautions. This shifts the system's functionality from simple diagnosis to decision support, enabling farmers to take appropriate corrective actions.

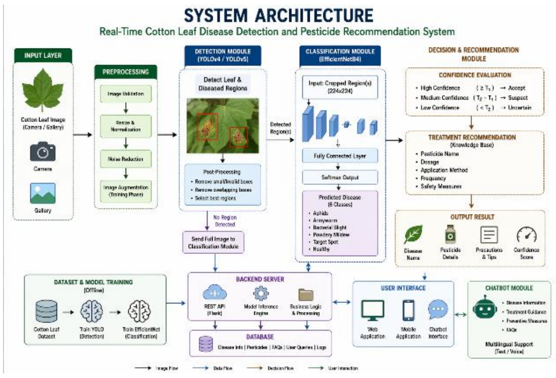
6. Conversational AI Integration

A chatbot interface is integrated to facilitate user interaction. Farmers can ask follow-up questions related to detected diseases, treatment methods, or preventive measures. The chatbot provides context-aware responses in a user-friendly and multilingual format, improving accessibility and user engagement.

7. System Deployment and Architecture

The system is implemented as a full-stack application with backend APIs for model inference and frontend/mobile interfaces for user interaction. It supports both cloud-based and edge deployment, allowing real-time predictions even in low-resource environments. The workflow includes image acquisition, detection, classification, result visualization, and advisory generation, forming a complete end-to-end solution.

IV. SYSTEM ARCHITECTURE



V. RESULTS & DISCUSSION

The proposed cotton leaf disease detection system was evaluated using a dataset containing six classes, including both healthy and diseased conditions. The EfficientNet-based classification model achieved an overall accuracy of approximately 98.03%, demonstrating its strong capability to distinguish between different disease categories. The confusion matrix (shown on page 32) indicates clear diagonal dominance, confirming that the model produces highly reliable predictions with only minor misclassification among visually similar diseases.

The YOLO-based detection module also showed effective performance in identifying relevant leaf regions. The model achieved a precision of 0.743, recall of 0.731, and mAP@0.5 of 0.786, indicating stable and practical detection capability. The Precision-Recall curve (page 31) reflects consistent performance across varying thresholds, while the F1-confidence curve suggests that optimal performance is achieved at a confidence level of approximately 0.38. The confusion matrix further confirms that the model can accurately localize plant regions, although some background confusion remains due to complex field conditions.

The integration of detection and classification into a two-stage pipeline significantly improves overall system performance compared to single-stage approaches. By focusing classification only on detected regions, the system reduces noise and enhances prediction accuracy. Additionally, the implementation of confidence-based decision logic helps identify uncertain or low-confidence predictions, thereby reducing the risk of incorrect recommendations in real-world scenarios.

Beyond prediction, the system provides practical value by offering pesticide recommendations based on the identified disease. This transforms the system from a simple diagnostic tool into a comprehensive decision-support solution. The inclusion of a chatbot interface further enhances usability by allowing users to interact with the system and receive context-aware guidance in an accessible manner.

Despite its strong performance, the system has certain limitations. Its accuracy may decrease under challenging conditions such as poor lighting, image blur, occlusion, or overlapping disease symptoms. Minor classification errors may also occur in cases where diseases share similar visual characteristics. However, these limitations can be addressed in future work through larger and more diverse datasets, improved model training, and enhanced preprocessing techniques

VI. CONCLUSION

This work presents a comprehensive and practical system for real-time cotton leaf disease detection and pesticide recommendation using deep learning and conversational AI. By integrating a YOLO-based detection model with an EfficientNet-based classification model, the system effectively identifies diseased regions and accurately classifies multiple cotton leaf conditions. The inclusion of confidence-aware decision logic enhances the reliability of predictions by addressing uncertainty and reducing the risk of incorrect outputs in real-world scenarios.

Beyond disease identification, the system provides actionable pesticide recommendations, including dosage and safety guidelines, thereby transforming it into a complete decision-support tool for farmers. The addition of a chatbot interface further improves usability by enabling interactive, context-aware guidance in an accessible manner. The system's ability to operate in real time and support both cloud and edge deployment makes it suitable for practical agricultural environments, including resource-constrained settings.

Experimental results demonstrate high classification accuracy and stable detection performance, confirming the effectiveness of the proposed approach. While certain challenges remain, such as performance under complex field conditions and dependency on dataset diversity, the system provides a strong foundation for AI-driven crop health management.

In conclusion, the proposed solution successfully addresses the need for an intelligent, scalable, and farmer-friendly platform for early disease detection and crop protection. It has the potential to improve agricultural productivity, reduce unnecessary pesticide usage, and support sustainable farming practices.

REFERENCES

[1] A. Pavate and N. Ansari, "Risk prediction of disease complications in type 2 diabetes patients using soft computing techniques," in *Proc. 5th Int. Conf. Advances in Computing and Communications (ICACC)*, Kochi, India, 2015, pp. 371–375.

[2] K. Moraye, A. Pavate, S. Nikam, and S. Thakkar, "Crop yield prediction using random forest algorithm for major cities in Maharashtra state," *Int. J. Innovative Research in Computer Science and Technology (IJIRCST)*, vol. 9, no. 2, 2021.

[3] N. S. Parvathaneni, M. F. Ijaz, and M. Woźniak, "XAI-driven model for crop recommender system for use in precision agriculture," *Computational Intelligence*, vol. 40, 2024.

[4] L. Goel, A. Jindal, and S. Mathur, "Design and implementation of a crop recommendation system using nature-inspired intelligence for Rajasthan, India," in *Deep Learning for Sustainable Agriculture*, Academic Press, 2022, pp. 109–128.

[5] L. Kaur and S. G. Sharma, "Identification of plant diseases and distinct approaches for their management," *Bulletin of the National Research Centre*, vol. 45, no. 169, 2021.

[6] "Global cotton supply and demand," MacroMicro.

[7] R. Nazeer *et al.*, "Detection of cotton leaf curl disease's susceptibility scale level based on deep learning," *Journal of Cloud Computing*, vol. 13, no. 50, 2024.

[8] M. M. Islam *et al.*, "A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture," *Intelligent Systems with Applications*, vol. 20, 2023.

[9] M. R. Ahmed, "Leveraging convolutional neural network and transfer learning for cotton plant and leaf disease recognition," *International Journal of Image, Graphics and Signal Processing*, vol. 13, no. 4, pp. 47–62, 2021.

[10] J. Zhang and W. Zhang, "Support vector machine for recognition of cucumber leaf diseases," in *Proc. Int. Conf. Advanced Computer Control*, Shenyang, China, 2010.

[11] C. Wang, J. Zhou, Y. Zhang, H. Wu, C. Zhao, G. Teng, and J. Li, "A plant disease recognition method based on fusion of images and graph structure text," Frontiers in Plant Science, vol. 12, Art. no. 731688, 2022, doi: 10.3389/fpls.2021.731688.

[12] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," Information Processing in Agriculture, vol. 4, no. 1, pp. 41-49, 2017.

[13] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," Global Transitions Proceedings, vol. 3, no. 1, pp. 305-310, 2022, doi: 10.1051/itmconf/20224403002.

[14] C. Zhou, S. Zhou, J. Xing, and J. Song, "Tomato leaf disease identification by restructured deep residual dense network," IEEE Access, vol. 9, pp. 28822-28831, 2021, doi: 10.1109/ACCESS.2021.3058947.

[15] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, "Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques," Computational Intelligence and Neuroscience, vol. 2019, Art. no. 9142753, 2019, doi: 10.1155/2019/9142753.

[16] S. Zhang, H. Wang, W. Huang, and Z. You, "Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG," Optik, vol. 157, pp. 866-872, 2018, doi: 10.1016/j.ijleo.2017.11.190.

[17] A. Krishnakumar and A. Narayanan, "A system for plant disease classification and severity estimation using machine learning techniques," in Proceedings of the Third International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2022, Hyderabad, India, 2019, pp. 393-405, doi: 10.1007/978-3-030-00665-5_45.

[18] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases

using deep convolutional neural networks," Neurocomputing, vol. 267, pp. 378-384, 2017, doi: 10.1016/j.neucom.2017.06.023.

[19] A. Prashanth and K. Sukanya, "Rice Leaf Diseases Classification Using CNN with Transfer Learning," in 2025 3rd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT), vol. 1, 2025, pp. 148–153.