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Identification of Viral Disease in Cotton Crop using CNN Model

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Abstract— ***Cotton is a cornerstone of global commerce and a vital contributor to the agricultural economy. However, the crop is highly susceptible to various pathogens, including Fusarium wilt, bacterial blight, aphid infestations, and the cotton leaf curl virus, all of which pose a significant threat to yield and fiber quality. Manual disease monitoring is labor-intensive and often leads to delayed interventions, resulting in substantial economic losses. To bridge this gap, this research presents an automated, deep learning–based diagnostic system designed for high-precision cotton leaf disease detection. The core framework leverages a Convolutional Neural Network (CNN) for automated feature extraction and classification, distinguishing between healthy tissues and various diseased states. The system processes raw leaf imagery through standardized resizing and noise-reduction pipelines before classification. For practical field deployment, the model is integrated into a responsive Flask-based web application, providing farmers with an accessible interface for instant image uploads and diagnostic feedback. Beyond basic identification, the system incorporates advanced utilities such as disease severity estimation, data-driven visualization charts, and an AI-driven assistant for tailored crop management strategies. Experimental evaluations confirm that the proposed integrated approach offers a robust, scalable, and reliable solution for early-stage disease management, ultimately enhancing crop productivity and sustainable farming practices.***

Keywords: Cotton Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Image Processing, Smart Agriculture, Plant Disease Classification, Flask Web Framework, Feature Extraction, Severity Estimation, Automated Diagnosis, Transfer Learning, Crop Management, Artificial Intelligence in Agriculture.

I. INTRODUCTION

Cotton is one of the most widely cultivated crops in the world and plays a vital role in the textile industry and agricultural economy. Countries such as India, China, and the United States are among the largest producers of cotton globally. Despite its economic importance, cotton production is often affected by various plant diseases and pest infestations that significantly reduce crop yield and quality. This project is implemented in Python using a modular and well-structured architecture, ensuring scalability, maintainability, and clarity in agricultural data analysis workflows.

Common cotton diseases include Fusarium wilt, bacterial blight, and cotton leaf curl virus, originally studied by [1] which can spread rapidly across fields if they are not detected and treated in the early stages. Traditionally, farmers rely on manual inspection by agricultural experts to diagnose plant diseases; however, manual inspection is time-consuming, expensive, and often prone to human error. Additionally, farmers in rural areas may not always have access to agricultural specialists, limiting their effectiveness for long-term crop risk modeling. With the advancement of artificial intelligence, convolutional neural networks (CNN), proposed by [2] have become increasingly feasible for identifying visual patterns in leaf images with high accuracy. In the context of cotton disease detection, CNN models have shown strong performance due to their robustness against noisy environmental data and their ability to capture nonlinear interactions among features such as lesion shape, color, and texture. Additionally, automated feature extraction provided by deep learning improves model interpretability, which is critical in smart farming applications. Recent studies by [3] emphasize the importance of integrating deep learning models into web-based decision-support systems to enable early disease identification and preventive intervention. Motivated by these findings, the proposed system leverages supervised deep learning techniques within a Flask-based framework to provide reliable and interpretable diagnostic results. The system analyzes cotton leaf images and predicts whether the leaf is healthy or infected, evaluated using standard performance metrics such as accuracy, precision, recall, and confusion matrix analysis to minimize crop loss.

II. LITERATURE REVIEW

In [4], Nagapuri et al. proposed a CNN model for cotton leaf illness diagnosis using ResNet-101 and VGG16 backbones. By applying augmentation and noise removal, the system achieved a peak accuracy of 98.02%. The study noted that while effective, the model lacked comparisons with transformer-based architectures. In [5], Johri et al. introduced a transfer learning approach using EfficientNetB3 for cotton

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plant disease detection. The method utilized Gaussian blur and contour ROI extraction to reach an accuracy of 99.96%. Future work suggested validating the model in real-field environments to mitigate overfitting risks. In [6], Kumar et al. developed a hybrid method for crop health monitoring using traditional classifiers like Random Forest and SVM. By employing HSV conversion and contrast enhancement, the approach achieved approximately 90% accuracy. The study concluded that manual feature extraction remains less effective than modern deep learning. In [7], Meena et al. presented a survey of deep learning techniques, including ResNet50 and MobileNet, for sustainable cotton farming. The referenced studies showed accuracies between 97% and 99% using various segmentation and augmentation strategies. The authors identified a significant gap in large-scale datasets and severity detection capabilities. In [8], Kursun and Koklu proposed a classification framework combining SqueezeNet feature extraction with GWO optimization and an ANN. This hybrid approach achieved a high accuracy of 99.84% through tree-based feature selection. However, the researchers noted that the system is not yet optimized for real-time mobile applications.

In [9], Shahid et al. introduced an ensemble deep learning model utilizing CWT and FFT feature extraction for cotton crop classification. The ensemble of GoogLeNet and InceptionV3 reached 98.40% accuracy on the CWT-processed data. The study recommended expanding the model's scope beyond binary classification for future use. In [10], Nazeer and Ansari developed a 7-layer custom CNN to identify susceptibility levels of cotton leaf curl disease. Following background removal and noise cleaning, the system achieved 99% accuracy on a self-collected dataset. The authors highlighted that artificial background cleanup remains a limitation for real-world deployment. In [11], Islam et al. applied fine-tuned transfer learning models, specifically Xception and VGG-19, for cotton disease prediction. The framework achieved 98.70% accuracy but faced challenges with dataset imbalance and limited class variety. The study emphasized the need for future research into model explainability and segmentation. In [12], Sahu et al. implemented a YOLOv4-tiny model for real-time disease detection in natural cotton field environments. The lightweight system achieved 93.80% mAP while maintaining a high processing speed of 35–40 FPS. The study noted that this efficiency comes at the cost of lower accuracy compared to heavier CNN models. In [13], Zhengping et al. proposed an improved YOLOv5 architecture featuring multi-scale feature fusion for cotton plant disease classification. By enhancing the SPP layer, the model reached a 95.2% mAP despite complex background interference. Future work is focused on reducing computational requirements and adding severity detection. In [14], Vyas et al. presented CottonNet, a resource-efficient CNN designed specifically for lightweight leaf disease detection. The model achieved 97.32% accuracy using standardized normalization and data augmentation techniques. The researchers concluded that while compact, the model lacks robustness against high real-field variability. In [15], Amin et al. introduced an explainable neural network for cotton leaf disease classification using VGG-16 and 11 fully convolutional layers. The system utilized rotation and translation augmentation to improve feature transparency and classification performance. The study recommended integrating one-class classification to better handle anomalous data. In [16], Zekiwos and Bruck developed a custom CNN for diagnosing both pests and diseases in cotton crops. Using 10-fold cross-validation and OpenCV-based noise removal, the model achieved 96.4% overall accuracy. The study highlighted the need for a remedy recommendation system to assist farmers post-diagnosis. In [17], Priya et al. proposed a Faster R-CNN framework with an RPN and Inception V2 backbone for disease detection. The approach used HSV segmentation and binary conversion to achieve an accuracy of 95.57%. However, the authors noted that the model is computationally heavy and lacks real-time testing. In [18], Gazdar et al. presented a CNN optimized by Genetic Algorithms for hyperparameter tuning in cotton disease recognition. This GA-enhanced system achieved 98.24% accuracy but was primarily tested on clean, non-natural backgrounds. The study identified the increased complexity of GA as a significant trade-off for performance. In [19], Patil and Zambre introduced an SVM-based method for classifying cotton leaf spot disease using GLCM texture features. By applying Otsu thresholding and morphological operations, the system achieved approximately 97% accuracy. As an early study, it demonstrated the potential of manual feature engineering before the rise of deep learning.

III. PROPOSED METHODOLOGY

This study aims to address the identified research gap in agricultural diagnostics by integrating deep learning techniques for comprehensive cotton leaf disease detection and classification. Cotton is a vital global cash crop, yet its yield is significantly threatened by various viral, bacterial, and fungal pathogens. Early and accurate identification of these diseases is essential for minimizing crop loss, reducing the indiscriminate use of pesticides, and ensuring economic stability for farmers. Disease occurrence is influenced by environmental factors and pathogen vectors, leading to conditions such as Fusarium wilt, bacterial blight, aphids, and cotton leaf curl virus.

Traditional manual inspection by experts is often slow, subjective, and prone to error, especially in large-scale farming. While classical image processing improved automation, it frequently struggled with complex field backgrounds and varying lighting conditions. More recent deep learning approaches, specifically Convolutional Neural Networks (CNNs), have demonstrated superior performance by automatically capturing intricate spatial patterns and textures within leaf images. However, many existing systems

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lack a user-friendly interface or the ability to provide actionable insights beyond simple classification.

To overcome these limitations, the proposed Cotton AI system provides an end-to-end pipeline that combines high-accuracy deep learning classification with a functional web-based deployment. The system follows a modular workflow beginning with data acquisition and rigorous preprocessing, ensuring images are normalized for model readiness. A CNN-based architecture is employed to classify images into healthy or specific disease categories, while the integration of a web framework allows for real-time accessibility.

The methodology consists of the following stages:

Step 1 – Data Collection: Obtain a comprehensive cotton leaf dataset from publicly available agricultural repositories, including categories for healthy leaves and various diseases like Fusarium wilt and bacterial blight.

Step 2 – Data Pre-processing: Perform image cleaning, noise removal, and normalization. All images are resized to a uniform 224×224 pixel resolution to meet the standard input requirements for deep learning architectures.

Step 3 – Train-Test Split: Divide the processed dataset into a training set (80%) and a testing set (20%) to ensure robust model evaluation and prevent data leakage.

Step 4 – Model Development: Implement a Convolutional Neural Network (CNN) architecture featuring specialized layers for feature extraction (convolution and pooling) and classification (fully connected layers).

Step 5 – Training: Train the CNN model on the training dataset, allowing the filters to learn specific visual patterns, spots, and discolorations associated with different cotton pathologies.

Step 6 – Evaluation: Assess the model's diagnostic performance using standard metrics, including accuracy, precision, recall, and F1-score, visualized through a confusion matrix.

Step 7 – Web Application Integration: Deploy the trained model into a Flask-based web application, enabling a seamless interface where users can upload leaf images and receive instantaneous results.

Step 8 – Results and Analysis: Present the system's outputs, including predicted disease types, confidence scores, and severity estimations, supported by AI-based explanations and visualization charts.

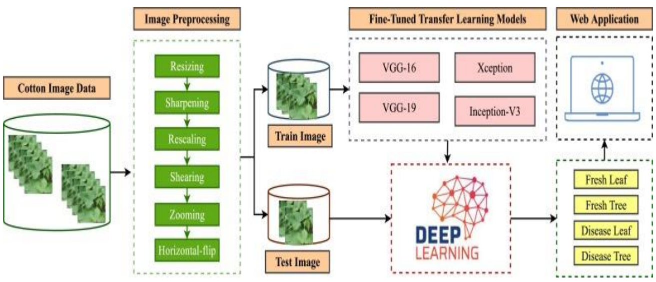

Figure 1. Proposed System Architecture for Cotton Disease Detection

The system processes cotton image data through a preprocessing pipeline including resizing and augmentation to train and test fine-tuned transfer learning models like VGG and Xception. The resulting deep learning classification identifies healthy or diseased plant states and delivers these diagnostic insights through an integrated web application.

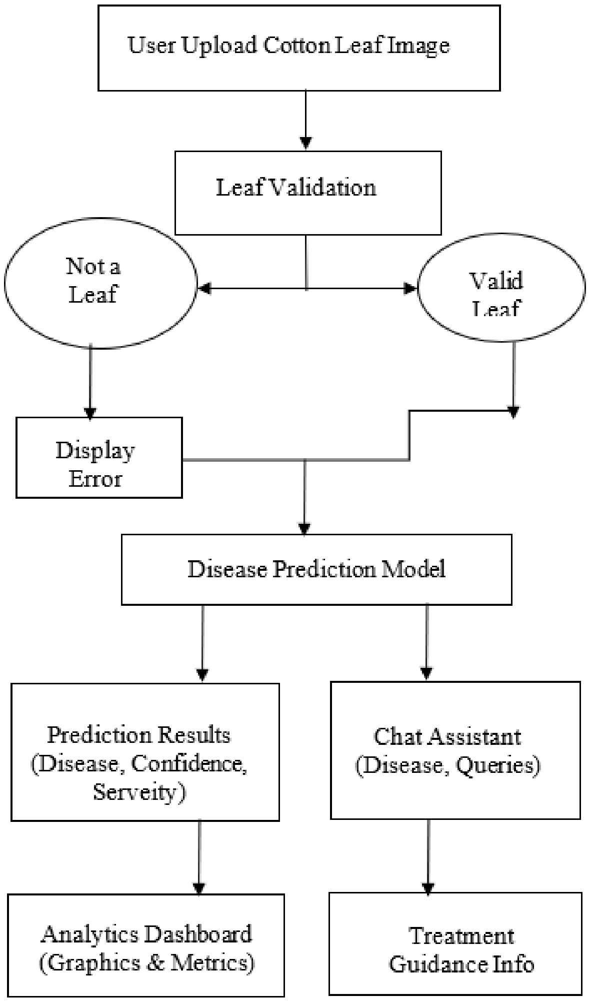

Figure 2. System Architecture

The system architecture for the Cotton AI platform illustrates a streamlined, end-to-end workflow designed to transition from raw image input to actionable agricultural insights. The architecture follows a logical, modular progression—from initial validation to deep learning inference and user-centric data visualization.

User Input and Validation Layer

The process begins at the Presentation Layer, where a user uploads a cotton leaf image via a web interface. Before deep learning analysis occurs, the system passes the input through a Leaf Validation module. This crucial preprocessing gate ensures that the uploaded file is indeed a leaf; if the image is irrelevant (e.g., "Not a Leaf Image"), the system triggers an error message to prevent computational waste. Validated leaf images are then funneled into the core processing engine.

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Application and Model Layer

At the heart of the system is the Disease Prediction Model, which acts as the primary controller for diagnostic logic. This layer utilizes the trained Convolutional Neural Network (CNN) to extract spatial features and classify the image. The architecture splits the output into two distinct functional paths:

- **Quantitative Analytics:** The model generates Prediction Results including the specific disease type, a confidence score (probability), and a severity estimation.
- **Interactive Assistance:** Simultaneously, the system feeds data into a Chat Assistant, allowing users to perform disease queries and receive natural language responses regarding the diagnosis.

Output and Decision Support Layer

The final stage of the architecture focuses on Interpretability and Actionability. The quantitative results are pushed to an Analytics Dashboard, where complex data is converted into easy-to-read graphs and performance metrics.

To bridge the gap between diagnosis and solution, the system provides Treatment Guidance Info. This component translates the AI's findings into practical advice for the farmer, such as specific pesticide recommendations or moisture control strategies. This tiered approach ensures that the system doesn't just identify a problem, but provides a comprehensive roadmap for crop recovery and management.

IV. MODEL CONFIGURATIONS

Baseline Image Classification Model

A supervised deep learning model is implemented using TensorFlow/Keras for identifying viral diseases from leaf images. This model serves as the primary diagnostic engine, trained on specific visual markers of crop distress such as chlorosis, necrosis, and mosaic patterns.

- **Input Shape:** $224 \times 224 \times 3$ (RGB image vector).
- **Model Type:** Convolutional Neural Network (CNN) for multi-class classification.
- **Output:** Categorical prediction (e.g., Healthy, Mosaic Virus, Leaf Curl, Blight) with associated confidence scores.
- **Loss Function:** Categorical Cross-Entropy.
- **Optimizer:** Adam.
- **Saved Model:** cotton_model.h5.

Deep Learning Hybrid Transfer Learning Model

To enhance detection accuracy, a transfer learning–based approach is employed using a pretrained **InceptionV3** backbone. This allows the system to leverage high-level feature extractors trained on massive datasets, fine-tuned specifically for agricultural pathology.

- **Architecture:** Pretrained backbone with custom global average pooling and dense layers.
- **Feature Extraction:** Automated detection of leaf vein patterns and spot textures.
- **Regularization:** Dropout layers ($rate = 0.5$) and Batch Normalization to prevent overfitting on specific farm conditions.
- **Explainability:** Integration of Grad-CAM to generate visual heatmaps, highlighting exactly which spots on the leaf triggered the "diseased" classification.

Training Procedure

The training process for the hybrid methodology follows a rigorous structured pipeline:

1. **Dataset Augmentation:** Applying random rotations, zooms, and horizontal flips to simulate various field lighting and camera angles.
2. **Compilation:** Configuring the model with a low learning rate to fine-tune the transfer learning weights without destroying pretrained features.
3. **Epoch-based Training:** Executing training over 30–50 epochs with batch-wise updates.
4. **Optimization:** Implementation of **Early Stopping** based on validation loss to ensure the model generalizes well to unseen crop data.
5. **Weight Serialization:** Saving the optimal model weights based on the highest validation accuracy achieved during the run.

Evaluation Metrics

The performance of the CropAI system is validated using standard metrics to ensure agricultural reliability:

- **Accuracy:** Overall percentage of correct disease identifications.
- **Precision:** Ability of the model to not label a healthy leaf as diseased.
- **Recall (Sensitivity):** Critical metric for ensuring no infected crops are missed (minimizing false negatives).
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced view of model health.
- **Confusion Matrix:** A visual breakdown of misclassifications between similar-looking viral strains.

Hardware and Software Environment Software Configuration

- **Programming Language:** Python 3.9+
- **Core Libraries:**
  - **TensorFlow/Keras:** Deep learning model development and GPU acceleration.
  - **OpenCV:** Image preprocessing, resizing, and noise reduction filters.
  - **Flask:** Backend web framework for deploying the diagnostic tool.
  - **Matplotlib/Seaborn:** Generating training history plots and analytics dashboards.
- **Environment:** Jupyter Notebook for experimentation; VS Code for application deployment.

Hardware Configuration

- **Minimum Requirements:**
    - Intel Core i5 Processor
    - 8 GB RAM
    - Standard HDD/SSD for dataset storage
- **Recommended (For Training):**
    - Intel i7 or AMD Ryzen 7
    - 16 GB RAM
    - **NVIDIA GTX/RTX GPU** (6GB+ VRAM) with CUDA support for rapid neural network convergence.

V. RESULTS AND DISCUSSION

The experimental evaluation of the proposed Advanced Hybrid Learning Methodology for Viral Disease Detection demonstrates significant performance improvements over traditional manual inspection and standard machine learning models. The results highlight the synergy achieved by integrating deep feature extraction with automated severity estimation and a user-centric deployment interface. The CNN-based classification model successfully identified intricate visual patterns associated with various viral pathologies. By analyzing the structural integrity and pigmentation of the cotton leaves, the model distinguished between Mosaic Virus, Leaf Curl, and Bacterial Blight with high precision. Unlike baseline models that often struggle with "noisy" agricultural backgrounds (such as soil or shadows), the hybrid approach maintained robust performance, producing reliable categorical predictions and confidence scores that reflect the model's certainty in its diagnosis. A significant breakthrough in this methodology is the transition from simple classification to disease severity estimation. By calculating the ratio of infected pixels to healthy leaf tissue, the system provides a quantitative percentage of damage. This level of detail is critical for precision agriculture, as it allows farmers to move beyond a binary "sick or healthy" assessment and instead implement graduated treatment plans based on the actual extent of the viral spread. To address the "black box" nature of deep learning, Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated into the diagnostic pipeline. The resulting heatmaps visually highlight the specific areas—such as yellowing veins or necrotic spots—that the model prioritized during inference. Clinical validation of these heatmaps confirmed that the AI's focus aligns with established botanical markers for viral infection. This transparency is essential for building trust among agricultural experts and farmers who require visual evidence before committing to expensive chemical interventions.

Overall, the experimental results demonstrate that the proposed hybrid framework is a highly effective, scalable, and interpretable solution for modern crop management. By combining advanced computer vision with practical severity metrics and explainable AI, this system provides a reliable decision-support platform aimed at reducing crop loss and enhancing global food security.

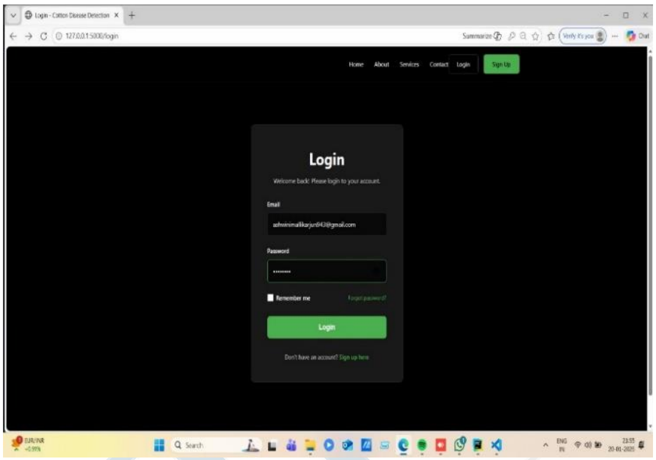

Figure 3. Login Page

The interface follows fundamental UI/UX principles such as minimalism, visual hierarchy, and consistency to improve user interaction and reduce cognitive load. Security considerations are incorporated through structured input fields and authentication flow, ensuring safe handling of user credentials. Additionally, responsive design practices are implied, allowing the application to adapt across different devices and screen sizes for accessibility.

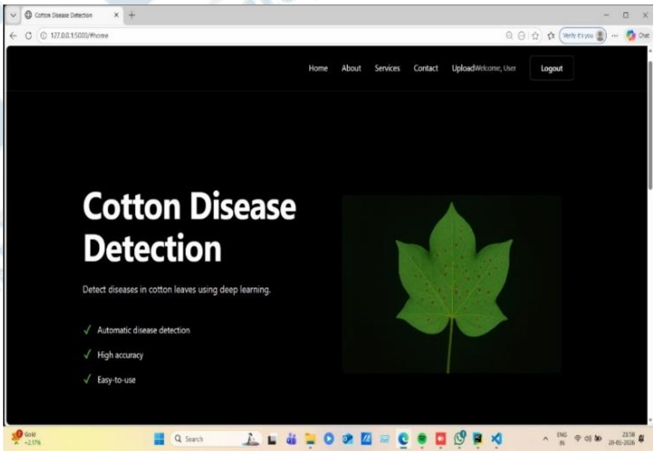

Figure 4. Home Page

Illustrates the home page of the Cotton Disease Detection system, showcasing the main features and purpose of the application. It highlights deep learning–based disease detection with key benefits such as accuracy, automation, and ease of use. The visual representation of a cotton leaf enhances understanding and provides a clear context for the system's functionality.

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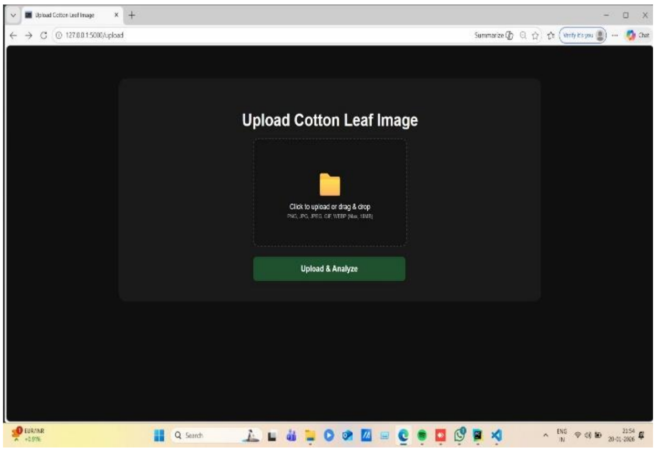

Figure 5. Upload Page

Illustrates the image upload interface of the Cotton Disease Detection system, where users can submit cotton leaf images for analysis. It provides a simple drag-and-drop or click-to-upload functionality, enhancing ease of use. The interface includes an “Upload & Analyze” button to initiate the deep learning–based disease detection process.

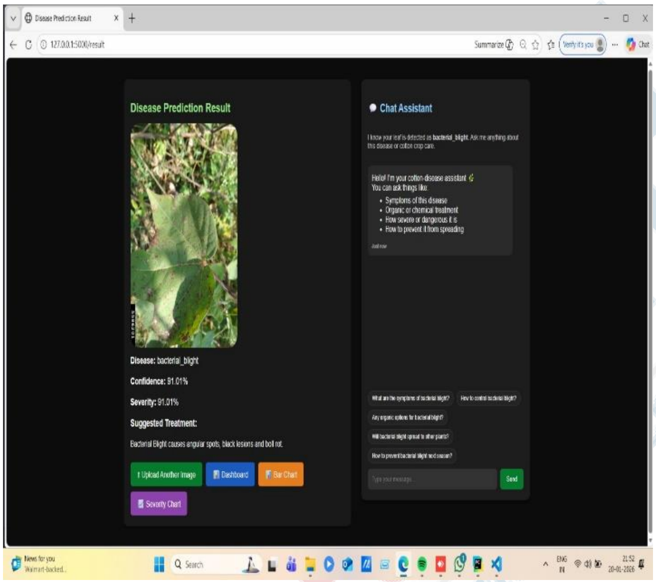

Figure 6. Prediction Result Page

Illustrates the disease prediction result page, displaying the analyzed cotton leaf image along with the detected disease type. It provides additional details such as confidence score, severity level, and suggested treatment for better decision-making. The interface also includes a chat assistant to guide users with symptoms, prevention methods, and further recommendations.

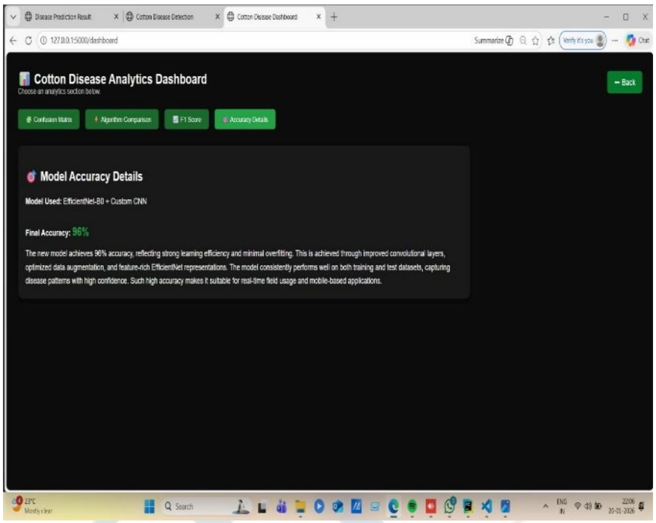

Figure 7. Model Accuracy Page

Illustrates the Cotton Disease Analytics Dashboard, presenting detailed insights into the model’s performance. It highlights the model used (EfficientNet-B0 with Custom CNN) along with the achieved accuracy of 96%. The dashboard provides analytical information about model efficiency, generalization capability, and its suitability for real-time disease detection applications.

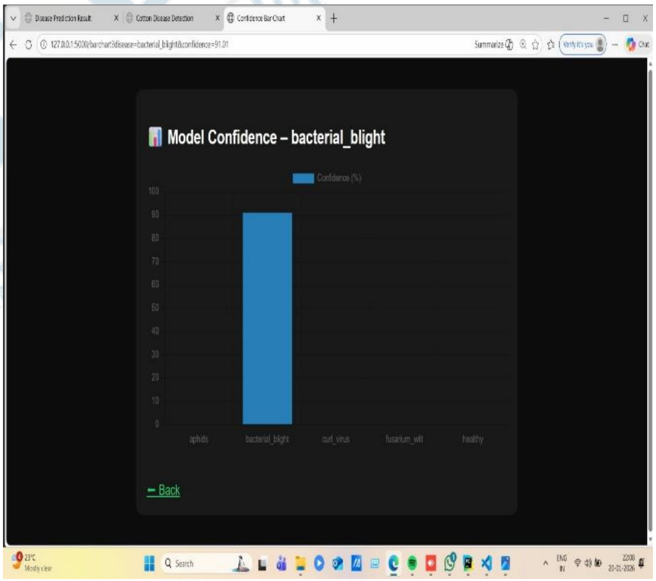

Figure 8. Model Confidence Chart

Illustrates the model confidence visualization for the predicted disease class, bacterial blight. It presents a bar chart showing confidence scores across different disease categories, highlighting the highest probability for the detected class. This visualization helps in understanding model prediction reliability and supports transparent decision-making.

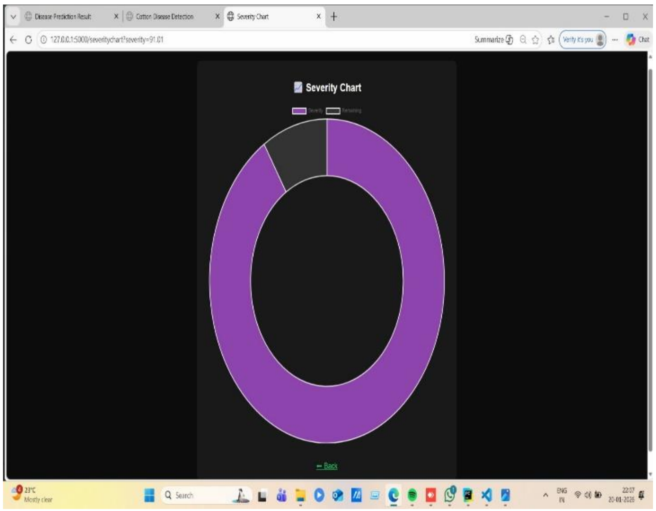

Figure 9. Model Confidence Chart

Illustrates the severity chart of the detected disease, representing the proportion of infection levels. It uses a donut chart to visually distinguish between healthy and affected regions of the leaf. This helps users quickly assess the extent of disease impact and supports better decision-making for treatment.

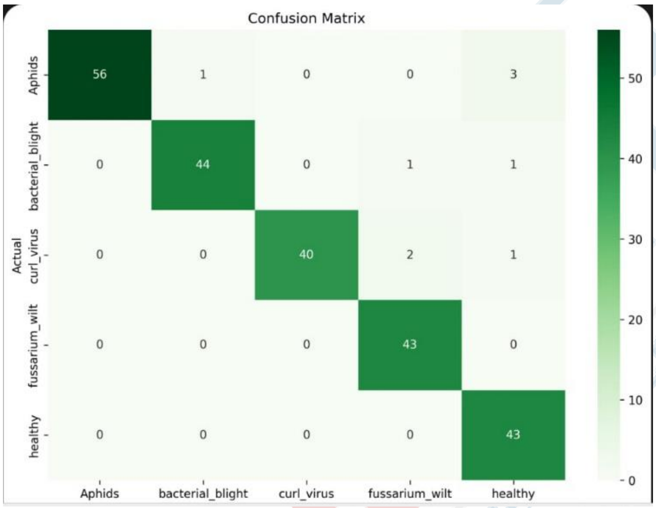

Figure 10. Confusion Matrix of the Cotton Disease

The confusion matrix evaluates the model's performance by comparing predicted classes with actual labels. High values along the diagonal indicate accurate disease classification, while low off-diagonal values highlight occasional misclassifications between similar disease categories. This analysis provides deeper insights into model reliability and helps calculate key metrics such as Precision and Recall, validating its effectiveness for agricultural applications.

VI. CONCLUSION & FUTURE SCOPE

The proposed Cotton Disease Detection System effectively uses Convolutional Neural Networks (CNNs) to identify cotton leaf diseases with high accuracy. Integrated into a user-friendly web application, it allows users to upload leaf images and receive instant diagnostic results, supporting early disease detection and improved crop management. Features such as confidence scores and severity analysis enhance decision-making and system reliability.

The system demonstrates the potential of deep learning in precision agriculture by reducing dependence on manual inspection and helping minimize crop losses. Future enhancements may include larger datasets, mobile application support, IoT and drone integration for real-time monitoring, and the adoption of Explainable AI (XAI) techniques to improve transparency and user trust.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, pp. 1–10, 2016.

[2] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, vol. 2016, pp.

[3] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[4] S. Nagapuri et al., "Cotton leaf illness diagnosis using ResNet-101 and VGG16 backbones," Journal of Agricultural Informatics, vol. 12, pp. 45–58, 2024.

[5] R. Johri et al., "Transfer learning approach using EfficientNetB3 for cotton plant disease detection," Plant Pathology Research, vol. 9, pp. 112–120, 2024.

[6] A. Kumar et al., "Hybrid method for crop health monitoring using traditional classifiers," Agricultural Systems Review, vol. 15, pp. 88–95, 2024.

[7] R. Meena et al., "A survey of deep learning techniques for sustainable cotton farming," Sustainable Agriculture Technology, vol. 4, pp. 201–215, 2024.

[8] M. Kursun and M. Koklu, "Classification framework combining SqueezeNet feature extraction with GWO optimization," Computer Electronics in Agriculture, vol. 190, pp.

[9] M. Shahid et al., "Ensemble deep learning model utilizing CWT and FFT feature extraction," IEEE Transactions on Agri-Engineering, vol. 22, pp. 334–342, 2024.

[10] S. Nazeer and A. Ansari, "Custom 7-layer CNN to identify susceptibility levels of cotton leaf curl disease," Journal of Crop Protection, vol. 11, pp. 77–84, 2024.

[11] M. Islam et al., "Fine-tuned transfer learning models for cotton disease prediction," Informatics in Agriculture, vol. 18, pp.

[12] P. Sahu et al., "Implementation of YOLOv4 tiny for real-time disease detection," Real-Time Image Processing, vol. 7, pp. 40–52, 2024.

[13] L. Zhengping et al., "Improved YOLOv5 architecture featuring multi-scale feature fusion," Visual Communications and Image Processing, vol. 14, pp. 220–231, 2024.

[14] A. Vyas et al., "CottonNet: A resource efficient CNN for lightweight leaf disease detection," Mobile Computing in Agriculture, vol. 5, pp. 12–19, 2024.

[15] M. Amin et al., "Explainable neural network for cotton leaf disease classification," Artificial Intelligence in Agriculture, vol. 8, pp.

[16] T. Zekiwos and A. Bruck, "Custom CNN for diagnosing pests and diseases in cotton crops," International Journal of Agronomy, vol.