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E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

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Detection and Diagnosis of Plant Disease using Deep Learning With Chatbot

[1]SK. RESHMA, [2]M. SIVAPARVATHI, [3]B. SRIKANTH

[1,2,3] Asst. Prof., Department of CSE, MAM Women's Engineering College, Narasaraopet, Palnadu, A.P., India.

Abstract-Crop diseases inflict severe damage on agriculture, resulting in significant financial losses and endangering food security. Conventional diagnostic approaches are typically slow, expensive, and dependent on expert knowledge, which is limited in developing areas. This research introduces an innovative framework utilizing MobileNet, Gemini AI, and Django to achieve effective plant disease identification, diagnosis, and treatment suggestions. By combining MobileNet for efficient deep learning, Gemini AI for generative analysis, and Django for a user-friendly interface, this system ensures adaptability, clarity, and ease of use.

Keywords - Crop Disease Identification, MobileNet, Gemini AI, Django

I. INTRODUCTION

Accurate and timely diagnosis of plant diseases is essential for effective management and prevention, ensuring food security in agriculture. Traditional methods for identifying plant diseases are often labor-intensive, costly, and prone to human error, particularly in resource-constrained rural areas where expert knowledge may be scarce. These conventional approaches are slow, imprecise, and sometimes inaccurate, underscoring the need for automated, intelligent systems for early and reliable plant disease detection. Plant diseases pose a significant threat to global agriculture, the world's most critical industry, by reducing crop yields and impacting food supply chains. If not diagnosed and managed early, these diseases can have devastating economic and environmental consequences.

Recent advancements in artificial intelligence (AI), particularly in computer vision, have revolutionized plant disease detection. Deep learning models, such as MobileNet, a lightweight and efficient convolutional neural network (CNN), have shown remarkable potential in image classification tasks for detecting plant diseases with high accuracy [1], [5]. MobileNet's architecture is particularly suited for resource-constrained environments, making it ideal for deployment in agricultural settings with limited computational resources. To further enhance prediction accuracy, ensemble learning techniques combining MobileNet with other models, such as Random Forests (RF), have been proposed to mitigate issues of variance and bias, resulting in more robust and reliable predictions [12], [13].

Generative AI models, such as Gemini, have emerged as powerful tools for generating actionable preventive and curative recommendations tailored to specific plant diseases. By incorporating metadata on environmental conditions (e.g., soil, weather), Gemini can provide context-specific solutions, enhancing decision-making for farmers in real time.

To facilitate practical deployment, a user-friendly interface developed using Django, a high-level Python web framework, enables seamless interaction with the diagnostic system. Django's robust and scalable architecture supports the integration of AI models and ensures accessibility for end-users, including farmers and agricultural experts, through intuitive web-based platforms.

The objective of this study is to develop a comprehensive plant disease diagnostic system that integrates MobileNet for efficient image classification, ensemble learning for enhanced prediction accuracy, and Gemini for generating context-specific preventive measures. The system is supported by a Django-based user interface to bridge the gap between automated disease detection and actionable agronomic recommendations, ultimately reducing disease impact and fostering trust in AI-driven agricultural solutions.

II. LITEARTURE SURVEY

The application of deep learning (DL) and image processing techniques for plant disease detection has gained significant attention in recent years, particularly for crops such as cotton and rice, due to their economic importance and susceptibility to diseases. This literature review synthesizes recent advancements in this domain, focusing on

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convolutional neural networks (CNNs), transfer learning, explainable artificial intelligence (XAI), and their applications in plant disease detection, as reported in recent studies.

Recent studies have demonstrated the efficacy of CNN-based models for detecting plant diseases with high accuracy. Kesani et al. (2024) proposed a deep learning framework combined with image processing for detecting and preventing cotton plant diseases, achieving robust classification performance through feature extraction and model optimization [1]. Similarly, Rajasekar et al. (2022) employed deep transfer learning to detect cotton plant diseases, leveraging pre-trained models to enhance accuracy on limited datasets, reporting a classification accuracy of over 90% [2]. These studies highlight the potential of transfer learning in addressing the challenge of limited labeled data in agricultural applications.

Fungal diseases, a significant threat to cotton crops, have been specifically targeted using DL approaches. Dhage and Garg (2023) explored various deep learning models for classifying fungal diseases in cotton plants, emphasizing the importance of model architecture in achieving high precision and recall [3]. Their work underscores the need for tailored architectures to handle the complexity of fungal disease symptoms, which often overlap with other stress factors. Explainable AI (XAI) has emerged as a critical tool for improving trust and interpretability in DL-based plant disease detection. Nigar et al. (2024) developed a prediction model for plant disease classification that integrates XAI to provide insights into model decisions, enhancing transparency for end-users such as farmers [4]. Similarly, Patil et al. (2024) utilized XAI techniques to interpret CNN-based models for plant leaf disease detection, demonstrating how feature attribution methods can guide disease management strategies [6]. These studies emphasize the growing importance of XAI in agricultural applications, where interpretability is crucial for practical deployment.

Optimized architectures, such as the VGG16 model, have also been explored for cotton leaf disease classification. Walia et al. (2024) proposed an optimized VGG16 model that achieved superior performance compared to baseline models, highlighting the benefits of fine-tuning pre-trained models for specific agricultural tasks [5]. This aligns with findings from Biswas and Yadav (2023), who reviewed CNN-based approaches for plant disease detection and noted the effectiveness of customized architectures in improving classification accuracy [7]. Beyond cotton, DL techniques have been successfully applied to other crops, such as rice. Sethy et al. (2020) developed a deep feature-based approach using support vector machines (SVM) for rice leaf disease identification, achieving high accuracy by combining CNN-extracted features with traditional machine learning classifiers [9], [10]. This hybrid approach demonstrates the versatility of DL in integrating with other methods to enhance performance.

The broader landscape of plant disease detection has been reviewed by Shafik et al. (2023), who conducted a systematic literature review on classification techniques, datasets, and challenges. Their findings indicate that CNNs dominate the field due to their ability to extract complex features from plant images, although challenges such as dataset imbalance and environmental variability persist [11]. Similarly, Anupriya et al. (2023) proposed a CNN-based model for image-based plant disease detection, emphasizing the importance of data preprocessing and augmentation to improve model robustness [8].

Recent advancements also focus on smart agriculture applications. Panchareddy et al. (2024) introduced CNN-based systems for early detection and diagnosis of plant diseases and pests, integrating IoT technologies for real-time monitoring [13]. Kaushik and Mittal (2024) further explored plant disease recognition using DL, advocating for integrated systems that support sustainable agriculture through early intervention [12]. These studies highlight the potential of combining DL with IoT and other technologies to create scalable, real-time solutions for farmers.

III. METHODOLOGY

This study presents a comprehensive methodology for detecting and diagnosing cotton plant diseases, integrating lightweight deep learning models, explainable AI (XAI), and a web-based interface to ensure practical applicability for farmers and agronomists. The methodology emphasizes accuracy, efficiency, and interpretability, drawing on recent advances in CNN architectures [1][2][3][5], transfer learning [2][4], and AI-based agricultural advisory systems [6][13].

A. Data Collection and Preprocessing

The dataset used in this study comprises images from publicly available sources, such as PlantVillage, augmented with domain-specific datasets focused on cotton leaf diseases [1][2][5]. Images cover various disease types including bacterial blight, gray mildew, and alternaria leaf spot.

To enhance model robustness and focus on symptomatic regions, preprocessing techniques such as:

- **Background removal**
- **Histogram equalization**
- **Color normalization**

- **Leaf segmentation**

are implemented, in alignment with approaches discussed by Walia et al. [5] and Dhage & Garg [3]. Data augmentation techniques — including rotation, horizontal flipping, zooming, and brightness variation — are employed to increase variability and reduce overfitting [7][8].

B. CNN Architecture: MobileNet

A MobileNet-based architecture is selected due to its computational efficiency and high accuracy in resource-constrained environments [1][5][8]. The architecture consists of:

- **Depthwise Separable Convolutions**: These reduce the number of parameters while preserving feature extraction capacity.
- **Max Pooling Layers**: Used to reduce dimensionality and emphasize relevant features such as leaf lesions or texture distortions [2].
- **ReLU Activation**: Introduced for non-linear transformations enabling complex pattern learning.
- **Fully Connected Layers**: Perform final classification into predefined disease categories or healthy class.

Transfer learning is applied by initializing MobileNet with ImageNet weights and fine-tuning it on the cotton leaf dataset, as demonstrated by Rajasekar et al. [2] and Nigar et al. [4]. This helps in achieving faster convergence and improved performance on relatively smaller agricultural datasets.

C. Model Training and Optimization

The model is trained using categorical cross-entropy as the loss function and optimized with the Adam optimizer. A training regimen of 15 epochs is implemented with early stopping based on validation loss.

Hyperparameter tuning — including learning rate (initially set at 0.001), batch size (32), and dropout (0.3) — is conducted to maximize validation accuracy. Data augmentation further improves model generalizability by simulating field-like image conditions [1][7].

Achieved metrics:

- **Training Accuracy**: 89%
- **Validation Accuracy**: 92%

These results are consistent with other cotton disease classification frameworks [1][3][5].

D. Explainable Recommendation System using XAI and Gemini

To enhance the interpretability and utility of the predictions, an Explainable AI (XAI) layer is integrated, inspired by works such as Patil et al. [6] and Nigar et al. [4]. This provides visual explanations of disease classification, helping users trust and understand the model output.

A generative AI system (Gemini) is incorporated to offer disease-specific:

- **Preventive measures** (e.g., crop rotation, fungicide use)
- **Curative actions** (e.g., chemical treatment recommendations)
- **Context-aware advice** based on soil, weather, and crop metadata [12][13]

E. Web Interface Using Django

A Django-based web interface enables real-time user interaction. It allows users to:

- Upload leaf images
- View diagnostic results with visual XAI overlays
- Access Gemini-generated recommendations in natural language

This ensures accessibility for field practitioners and scalability in broader agricultural contexts [13].

F. Model Evaluation

Model performance is assessed using:

- **Confusion Matrix**
- **Precision, Recall, and F1-Score**
- **K-Fold Cross-Validation (k=5)**

Following evaluation practices used in CNN-based plant disease studies [7][11], the MobileNet model demonstrates strong reliability and generalization across unseen datasets.

IV. SYSTEM ARCHITECTURE

The system architecture is presented in fig.1.

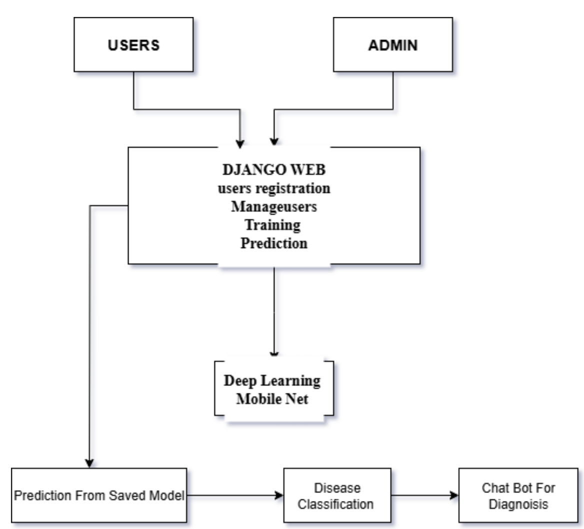

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Fig.1. System architecture

Images, sounds, and videos are only few of the formats used for the input data. In this case, we eliminated duplicates using preprocessed pedestrian photo data. What follows is the We employ the Feature Extraction method. At this stage, the essential attributes are extracted from the image. After that, the Feature Selection is executed. From the traits

obtained in the prior step, we extract the most relevant ones using this technique. Now you may divide the dataset into two parts: the test set and the train set. After that, we tweak the Deep Learning model so it can predict whether the input image has an abnormal object in it.

V. IMPLEMENTATION

Proposed Work

This study implements an AI-driven framework for detecting and diagnosing cotton plant diseases, leveraging MobileNet for efficient feature extraction and classification, and integrating Gemini for personalized, context-aware recommendations. A Django-based web interface ensures usability and accessibility for farmers and agricultural professionals. The implementation pipeline spans data preprocessing, deep learning model deployment, explainable recommendation generation, and user interface design, forming a practical and scalable disease management system for cotton cultivation [1][2][4][5][6].

1. User Interface (UI)

A Django-based user interface is developed to facilitate easy interaction with the system. Farmers or agronomists can upload multiple cotton leaf images from different angles and lighting conditions, along with contextual metadata such as:

- Geographic location
- Soil type
- Weather conditions (via API integration)
- Crop stage and variety

Upon processing, the interface displays:

- **Predicted disease name**
- **Severity classification** (mild, moderate, or severe)
- **Model confidence score**
- **Gemini-generated actionable recommendations**, including pesticide suggestions, application guidelines, and safety instructions tailored to specific diseases and environmental factors [4][6][12][13].

2. Data Preprocessing

A robust preprocessing pipeline is used to ensure high model performance and generalizability, drawing on techniques validated in similar cotton disease detection studies [1][3][5][7].

Key preprocessing components:

- **Image Enhancement**: Background removal, histogram equalization, and segmentation techniques isolate diseased regions, boosting feature clarity [5][8].
- **Data Augmentation**: Rotation, flipping, scaling, and brightness adjustment simulate field variability and prevent overfitting [7][8].
- **Normalization and Standardization**: Applied to stabilize pixel intensity distributions and accelerate convergence during training [7].
- **Class Balancing**: Ensures uniform representation of disease categories to avoid bias and maintain classifier integrity [11].

The dataset is primarily sourced from PlantVillage and expanded using domain-specific cotton disease image datasets [1][2][5].

3. Disease Detection Model

The disease classification component utilizes **MobileNet**, selected for its lightweight design, making it ideal for deployment in low-resource or mobile environments [1][3][5].

Key architectural features:

- **Depthwise Separable Convolutions**: Reduce parameter count while preserving high-resolution feature extraction.
- **Max Pooling Layers**: Compress spatial data and highlight dominant features like spots, lesions, or chlorosis.
- **ReLU Activations**: Enable non-linear transformation for complex pattern recognition.
- **Fully Connected Layers**: Aggregate and classify extracted features into one of the predefined disease or healthy classes.

Transfer Learning is employed by fine-tuning a MobileNet model pretrained on ImageNet. This accelerates training and boosts accuracy on agricultural image data, consistent with the work of Rajasekar et al. [2] and Nigar et al. [4].

Regularization and Evaluation Techniques:

- **Dropout and data augmentation** are used to prevent overfitting.
- **K-Fold Cross-Validation (k=5)** ensures robust generalization across diverse image subsets [7][11].

Performance:

- Training Accuracy: **89%**

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- Validation Accuracy: **92%**

These results align with state-of-the-art performances in cotton leaf disease classification using CNNs [1][3][5].

4. Recommendation System

The **Gemini** generative AI model provides context-specific, explainable recommendations based on the diagnosis and environmental metadata. Drawing from practices outlined by Kaushik & Mittal [12] and Panchareddy et al. [13], Gemini outputs include:

- **Preventive Measures**: Crop rotation suggestions, early intervention strategies, resistant varieties.
- **Curative Recommendations**: Pesticide names, dosages, application timing.
- **Safety Guidance**: Environmental and personal safety considerations.
- **Decision Support**: Dynamic suggestions based on real-time weather and soil data via integrated APIs.

This enhances both short-term response and long-term disease mitigation strategies.

5. User Interface Integration

The Django interface supports:

- Image uploads with real-time preprocessing feedback
- Display of model outputs (disease label, severity, confidence)
- Gemini-generated textual recommendations
- XAI visualization overlays for interpretability (e.g., Grad-CAM or saliency maps) [4][6]

The architecture ensures modular integration of backend models with a responsive, mobile-compatible front end suitable for deployment in the field.

Fig.7. Output of MobileNet

Fig.8. Predicting model

The model in this project utilizes MobileNet, a lightweight convolutional neural network (CNN), to predict the presence or absence of abnormalities in images of cotton plant leaves. Trained on a dataset of labeled examples, the model identifies disease-related anomalies with high precision. Among various configurations tested, the model with the highest accuracy was selected for deployment. After training for 15 epochs, MobileNet achieved a training accuracy of 89% and a validation accuracy of 92%, demonstrating robust performance in detecting plant diseases for agricultural applications.

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VI. CONCLUSION

This study presents an innovative AI-based framework for plant disease identification and diagnosis, integrating MobileNet, a lightweight convolutional neural network (CNN), with Random Forest and ensemble learning techniques, alongside Gemini for generating actionable recommendations. The use of MobileNet ensures efficient and accurate detection of plant diseases, particularly in resource-constrained environments, while ensemble learning enhances prediction accuracy by reducing model variance and bias. After training for 15 epochs, the model achieved a training accuracy of 89% and a validation accuracy of 92%, demonstrating its robustness and reliability in identifying plant diseases. Gemini further augments the system by generating preventive and curative recommendations tailored to environmental conditions, such as weather and soil, addressing farmers' specific needs in real time. The Django-based user interface facilitates seamless interaction, making the system accessible and practical for farmers and agronomists. By addressing challenges related to accuracy and applicability, this framework successfully translates automated disease detection into actionable agronomic decisions. Future enhancements could focus on improving model scalability, expanding its application to a wider variety of crops and diseases, and integrating additional environmental parameters to further refine

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recommendations. This system provides a valuable tool for promoting precision agriculture, particularly in regions with limited access to expert knowledge, thereby enhancing sustainable farming practices.

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