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Robust Crop Disease Detection and Management System using Deep Learning

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ABSTRACT
Agriculture is a vital sector for food security and economic stability, yet crop diseases pose a significant threat to yield to yield and quality. Early and accurate disease detection is crucial for effective disease management. This research presents a Crop Disease Detection and Management System utilization a MobileNetV2 based CNN for plant disease identification through image analysis. The system dynamically selects the appropriate model based on the users crop selection, processes the uploaded image and provides disease diagnosis results. Additionally offers preventive measures, treatment recommendation, and fertilizer suggestions. Diagnosed results are stored in a user dashboard for future reference. The proposed system aims to enhance agricultural productivity by providing an accessible, AI-driven solution for farmers and agriculturists.
Keywords – Disease Detection, MobileNet,Deep Learning, CNN

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I. INTRODUCTION

Agriculture plays a vital role in global food security and economic stability, yet it faces significant challenges due to crop diseases that lead to substantial yield losses. Early and accurate disease detection is crucial for mitigating these losses and ensuring sustainable farming practices. Traditional methods of disease identification rely on manual inspection, which is time-consuming, labor-intensive, and prone to errors. Recent advancements in artificial intelligence (AI) and deep learning have enabled the development of automated solutions for crop disease detection. In this project, we propose a **deep learning-based Crop Disease Detection and Management System** that leverages **MobileNet** for fast and efficient disease classification. Our system focuses on four major crops—**grape, pomegranate, sugarcane, and cotton**—using Kaggle-sourced datasets to train separate models for each crop.

Our Web-based application provides a user-friendly interface where farmers can upload an image of a crop leaf and select the corresponding crop type. The system then processes the image using the respective pre-trained **MobileNet model** to determine whether the crop is **healthy or diseased**. If a disease is detected, the model identifies the specific disease and provides confidence scores for the classification. Additionally, the system suggests **preventive measures and treatment solutions**, such as suitable fertilizers and disease management strategies, to help farmers take timely action. By integrating deep learning with practical agricultural solutions, this project aims to bridge the gap between AI-driver disease diagnosis and real-world farming applications, ultimately promoting healthier crops and improved yield outcomes.

II. LITERATURE SURVEY

This paper presents a CNN-based approach for detecting plant diseases using image processing techniques. It specifically focuses on pomegranate crops and discusses the segmentation of infected regions, followed by classification using convolutional neural networks. The study highlights the importance of early disease detection and proposes an Android-based solution for farmers to identify and manage crop diseases efficiently. [1]

This paper provides a comprehensive review of deep learning techniques such as CNN, RNN, and GANs for detecting crop diseases. The study discusses dataset challenges, image preprocessing techniques, and the role of transfer learning in improving model performance. [2]
This study presents an extensive review of image-based disease detection methods, including supervised learning, unsupervised learning, and hybrid models. It also addresses major challenges such as dataset imbalance, environmental variations, and occlusions in crop images. [4]

Haider et al. (2020) presented a deep learning-based approach for the early detection of wheat diseases using Convolutional Neural Networks (CNNs). Their study highlighted the limitations of traditional manual detection methods, which are prone to errors and time-consuming. The proposed system used a dataset of 2,100 images obtained from online sources and achieved significant accuracy in identifying five major wheat diseases. This study demonstrated how AI-powered mobile and web-based applications could support farmers by providing timely disease management solutions.

Bhargava et al. (2024) conducted a comprehensive review of plant disease detection techniques using computer vision and AI. Their research emphasized the role of machine learning (ML), deep learning (DL), and few-shot learning (FSL) in automating disease identification from plant leaf images. The study explored various image segmentation, feature extraction, and classification techniques used in plant disease detection, along with molecular diagnostic tools. The findings indicated that deep learning models, particularly CNNs, have outperformed conventional ML approaches due to their ability to extract intricate features from image datasets.

Kulkarni (2018) proposed a deep learning model for crop disease detection by leveraging transfer learning with MobileNet and InceptionV3 architectures. The model was trained on the PlantVillage dataset, containing over 54,000 images classified into 38 different classes. The study demonstrated that preprocessing techniques, including segmentation and grayscale conversion, significantly improved classification accuracy. Experimental results showed that InceptionV3 outperformed MobileNet in detecting various crop diseases, achieving an accuracy of over 99%.

Sharath et al. (2020) developed an Android-based application that uses CNN for plant disease detection. Their methodology included image processing techniques such as GrabCut segmentation and Gaussian filtering to enhance image quality before classification. The study focused on identifying diseases in horticultural crops like pomegranate and citrus fruits, which are highly susceptible to infections. The proposed system provided early disease detection along with treatment recommendations, thus aiding farmers in improving productivity and reducing losses.

III. Proposed System

The proposed system employs a deep learning-based approach to identify diseases in crops through image processing. The overall architecture consists of the following steps:

A. **Image Acquisition and Preprocessing**

- Images of infected and healthy crops are collected from agricultural datasets.
- Image augmentation techniques such as rotation, scaling, and contrast adjustment enhance model generalization.
- Images are resized and normalized for optimal CNN performance.

B. **Segmentation and Feature Extraction**

- GrabCut segmentation is used to extract the region of interest (ROI) from the input images.
- Morphological processing removes noise and refines extracted features.
- Edge detection techniques enhance disease visibility in segmented images.

C. **CNN-Based Classification**

- A deep CNN model is trained on labeled datasets containing various crop diseases.
- Features such as leaf texture, color variations, and lesion patterns are analyzed.
- The model classifies the images into predefined disease categories.

D. **Web-Based System Deployment**

- Frontend developed using React and Tailwind CSS ensures a responsive user interface.
- Flask/Django backend hosts the trained CNN model for real-time inference.
- An API fetches recommended treatments based on detected diseases.

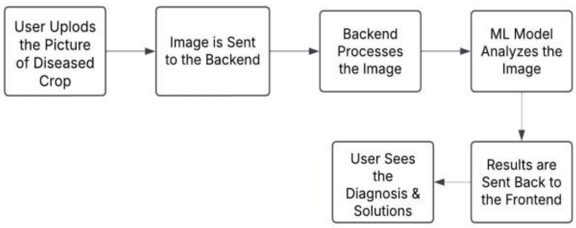

Fig.1.Block Diagram of Disease Diagnosis System

V. Results and Analysis

The CNN model was trained on a dataset comprising multiple crop disease images and achieved high accuracy in classification. Performance metrics such as precision, recall, and F1-score were used to evaluate the model's effectiveness. The web-based system allowed users to upload images, receive real-time diagnoses, and access treatment recommendations. Future improvements include expanding the dataset, refining segmentation techniques, and incorporating real-time IoT-based disease monitoring.

Comparison of our models with existing models in terms of accuracy:

Crop	Existing Model Accuracy	Current Model Accuracy
Grape	91%	98%
Cotton	92%	94%
Sugarcane	88%	91%

Pomegranate	91%	98%

Table.2 Comparison Table of existing models and our system

Dataset: We used a multiple dataset from Kaggle for the respective crops. Total number of images in Sugarcane dataset are 2600, Cotton dataset are 5760,12000 in Grape dataset. Combining all the images we have in total 20360 images.

1.Sugarcane

Disease	**Training/Testing/val Images**	**Total images**
Rust	411/52/51	514
Yellow	404/50/50	504
Mosaic	369/47/46	462
RedRot	414/52/52	518
Total		1998

Table.1. Number of images of Sugarcane

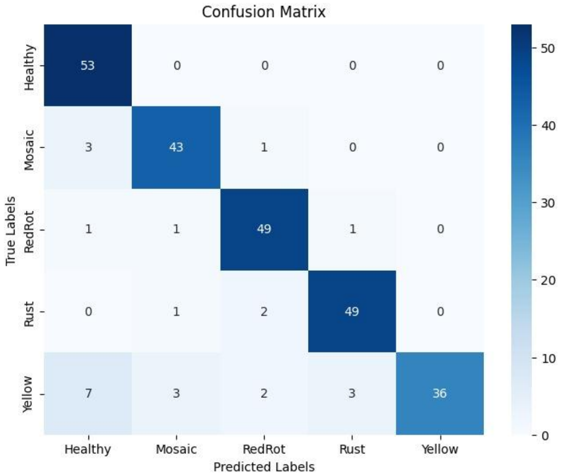

Fig.1.Confusion Matrix of Sugarcane

2.Grape

Disease	**Training/Testing Images**	**Total images**
ESCA	2400/600	3000
Leaf Blight	2400/600	3000
Black Rot	2400/600	3000
Total		9000

Table.2 Number of images of Grape

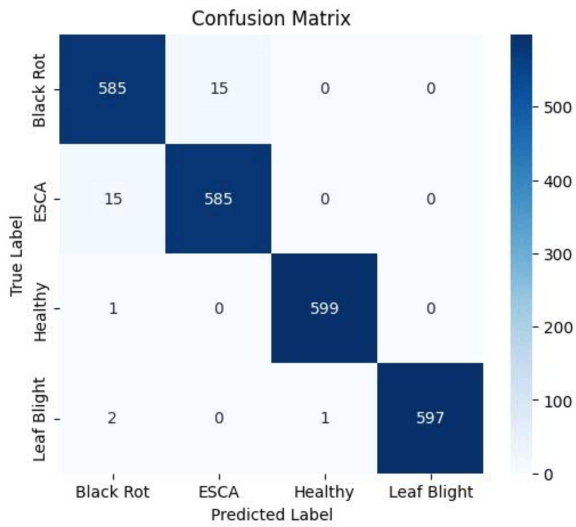

Fig.2.Confusion Matrix of Grape

3.Cotton

Disease	**Training/Testing Images**	**Total images**
Army_worm	1152/288/120	1560
Bacterial_Blight	1152/288/120	1560
Powdery_Mildew	1152/288/120	1560
Aphids	1152/288/120	1560
Target_spot	1152/288/121	1561
Total		7801

Table.2 Number of images of Cotton

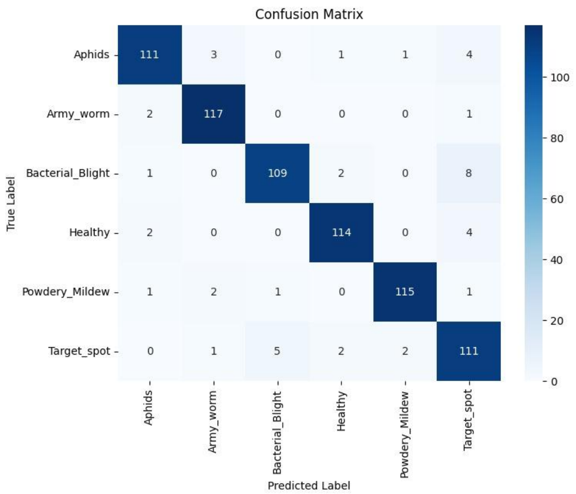

Fig.3.Confusion Matrix of Cotton

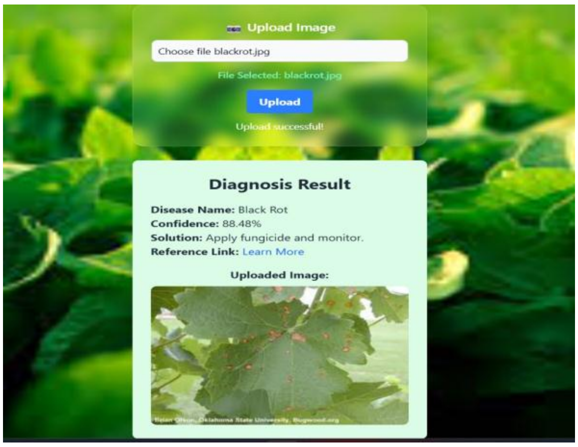

Fig.4.Diagnosis Result (Diseased)

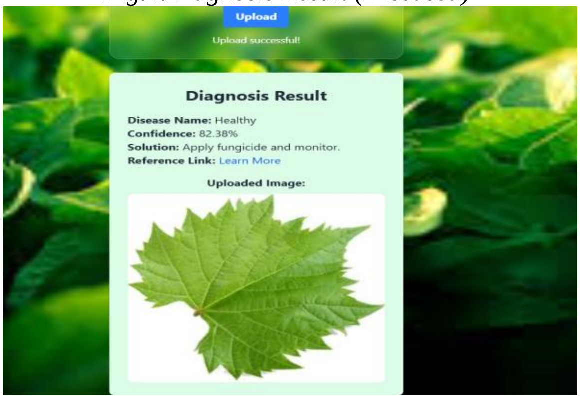

Fig.5.Diagnosis Result (Healthy)

Fig.6.Diagnosis Result (diseased)

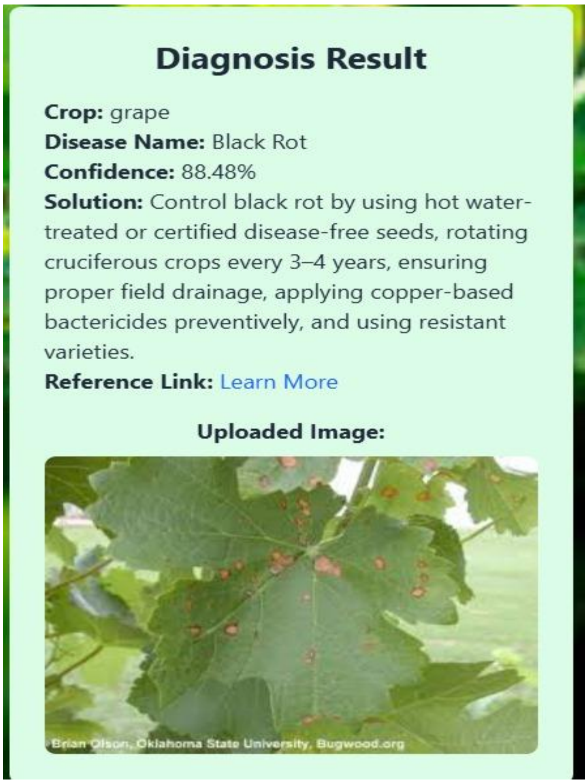

Fig.7.Diagnosis Result (diseased)

Fig.8.Diagnosis Result (diseased)

Fig.9.Diagnosis Result (Healthy)

V. Conclusion

The proposed Crop Disease Detection and Management System leverages MobileNet and deep learning to provide an efficient and accurate method for identifying diseases in grape, pomegranate, sugarcane and cotton crops. The System offers automated diagnosis, confidence scores, treatment recommendations, enabling farmers to take timely preventive measures. While it improves disease detection, limitations such as dataset automated crop recognition, real-time monitouring, and integration with weather and soil data to enhance precision and scalability. This work contributes to AI-driven precision farming, promoting sustainable agriculture.

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