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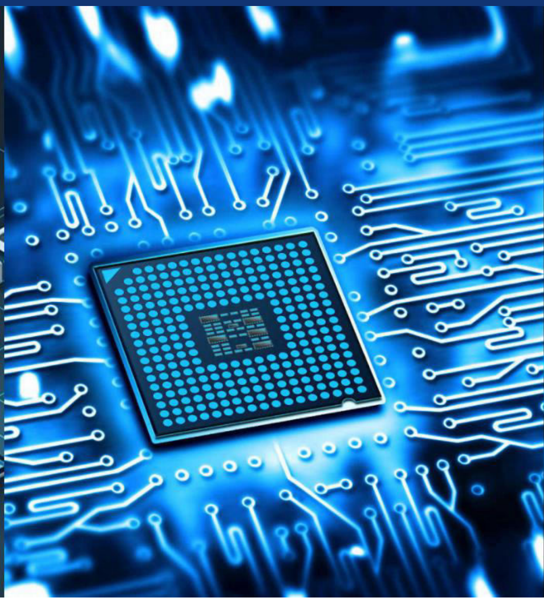


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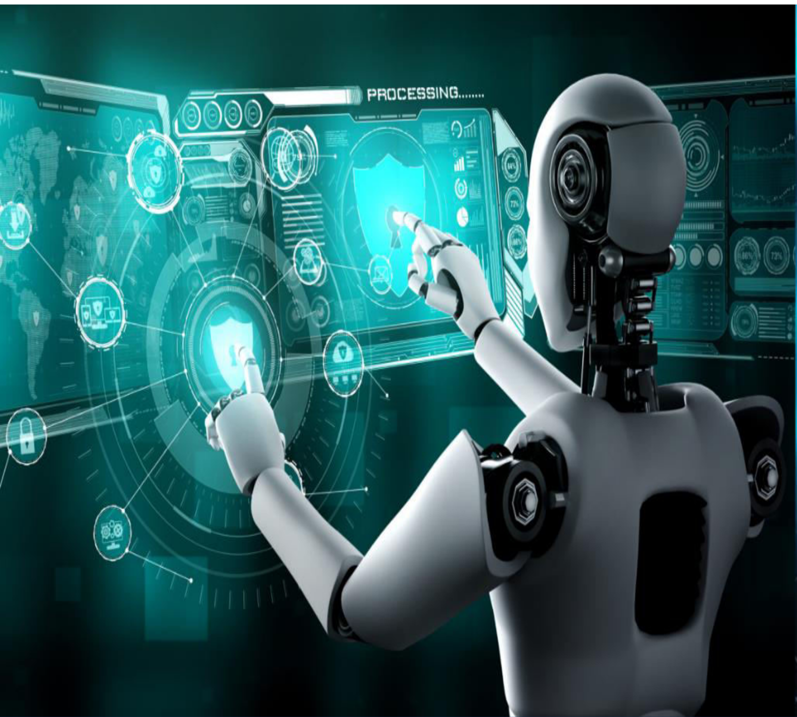

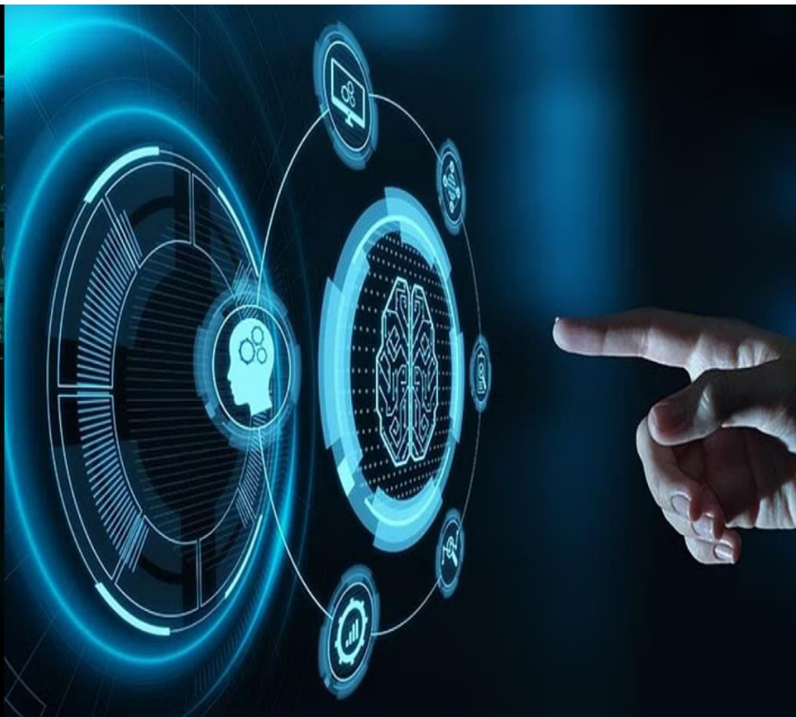

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Leaf Disease Detection Using Deep Learning

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ABSTRACT: Plant diseases significantly affect agricultural productivity and crop quality. Early and accurate disease detection is essential for improving crop yield and reducing economic losses. This paper presents a **Plant Leaf Disease Detection and Recommendation System Using Deep Learning** The proposed model simultaneously identifies the plant species and detects the corresponding leaf disease from an input image. The system is developed using **PyTorch** and deployed through a **Flask** web application for real-time disease prediction. In addition to disease classification, it provides treatment recommendations, preventive measures, and pesticide suggestions. The lightweight MobileNetV3 architecture ensures high accuracy with low computational cost, making the system suitable for precision agriculture and real-time farming applications.

KEYWORDS: Plant Leaf Disease Detection, MobileNetV3, Deep Learning, Multi-Task Learning, PyTorch, Flask, Precision Agriculture.

I. INTRODUCTION

Agriculture is one of the most important sectors for ensuring food security and economic growth. Plant diseases significantly affect crop yield and quality, leading to financial losses for farmers. Traditional disease identification methods rely on manual inspection by experts, which can be time-consuming and less accessible in rural areas.Recent advancements in Deep Learning and Computer Vision have enabled automatic plant disease detection using leaf images. This paper proposes a **Plant Leaf Disease Detection and Recommendation System Using Deep Learning** The proposed system simultaneously identifies the plant species and detects the corresponding disease from a leaf image. It also provides treatment recommendations and preventive measures through a Flask-based web application. The lightweight MobileNetV3 model ensures accurate and real-time disease prediction, making the system suitable for smart agriculture and precision farming applications.

II. LITERATURE REVIEW

Recent studies have shown that deep learning techniques significantly improve the accuracy of plant leaf disease detection. Pre-trained CNN models such as MobileNetV3, ResNet, and EfficientNet are widely used for disease classification. However, many existing systems focus only on disease prediction and do not provide treatment recommendations. The proposed system addresses this limitation by combining multi-task learning with a recommendation module for real-time agricultural support.

III. PROBLEM STATEMENT

Manual identification of plant diseases is time-consuming, costly, and requires agricultural expertise. Existing automated systems often have high computational requirements and limited real-time applicability. Therefore, an efficient and lightweight system is required to accurately identify both plant species and leaf diseases while providing treatment recommendations.

IV. PROPOSED SYSTEM

The proposed system uses a MobileNetV3-based multi-task deep learning model to identify plant species and detect leaf diseases from a single image. The system is deployed using Flask and provides real-time predictions along with disease information, prevention methods, and pesticide recommendations.

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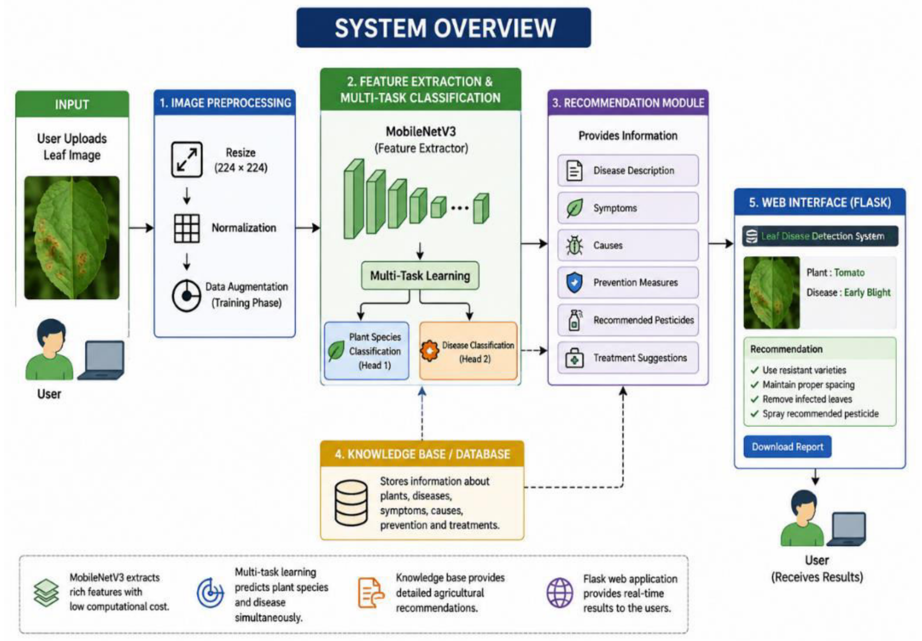

V. METHODOLOGY

The methodology consists of image acquisition, preprocessing, feature extraction using MobileNetV3, multi-task classification, disease prediction, and recommendation generation. The uploaded image is resized, normalized, and processed to produce accurate predictions in real time.

VI. SYSTEM ARCHITECTURE

The proposed architecture consists of Image Input, Image Preprocessing, MobileNetV3 Feature Extraction, Multi-Task Classification, Disease Recommendation Database, and Flask Web Interface. The extracted features are used to identify both the plant species and disease, after which treatment recommendations are displayed.

VII. MODULES DESCRIPTION

User Module: Uploads plant leaf images and views prediction results.
Preprocessing Module: Resizes and normalizes input images for better model performance.
Classification Module: Identifies the plant species and disease using the MobileNetV3 model.
Recommendation Module: Displays disease causes, prevention methods, pesticides, and treatment suggestions.

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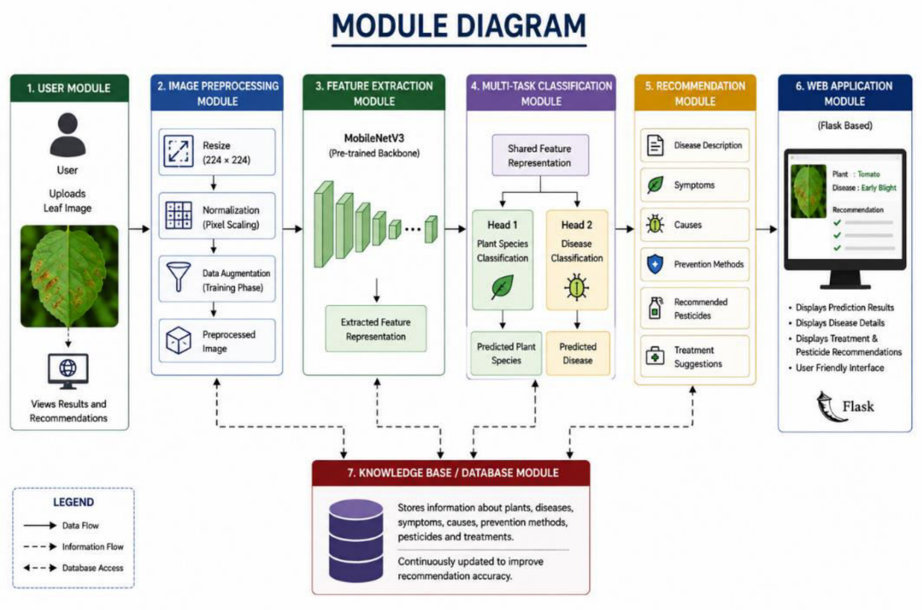

VIII. MOBILENETV3 & MULTI-TASK LEARNING ALGORITHMS

MobileNetV3 is a lightweight convolutional neural network designed for efficient image classification. The proposed system uses MobileNetV3 as the feature extractor and applies multi-task learning to simultaneously predict plant species and disease type. This approach improves computational efficiency and prediction accuracy.

IX. DATASET DESCRIPTION

The dataset consists of labeled plant leaf images representing multiple plant species and disease categories. Both healthy and infected leaf images are included to train and evaluate the deep learning model effectively.

X. IMPLEMENTATION DETAILS

The system is implemented using Python and PyTorch. Flask is used for web deployment, while Pillow is used for image preprocessing. The trained MobileNetV3 model performs real-time inference and displays prediction results through a web interface.

XI. EXPERIMENTAL SETUP

The model is trained and tested using a labeled leaf image dataset. Images are resized to 224×224 pixels before training. Performance is evaluated using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix metrics.

XII. EXPERIMENTAL RESULTS & PERFORMANCE EVALUATION

The proposed model achieved high classification accuracy for both plant and disease prediction. The lightweight MobileNetV3 architecture reduced inference time while maintaining reliable performance. Experimental results demonstrate the effectiveness of the proposed system for real-time agricultural applications.

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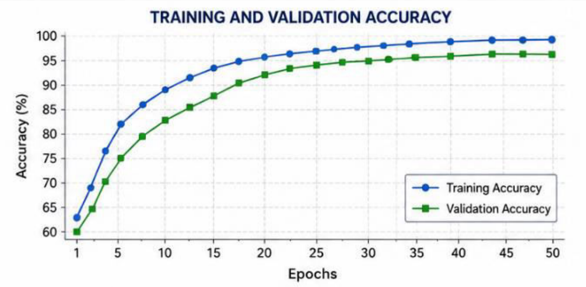

Fig. 1. Training and validation accuracy of the proposed MobileNetV3 multi-task model.

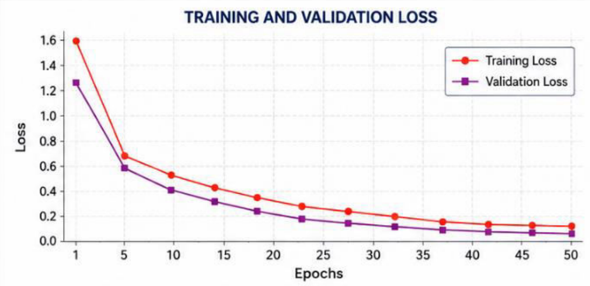

Fig. 2. Training and validation loss of the proposed MobileNetV3 multi-task model.

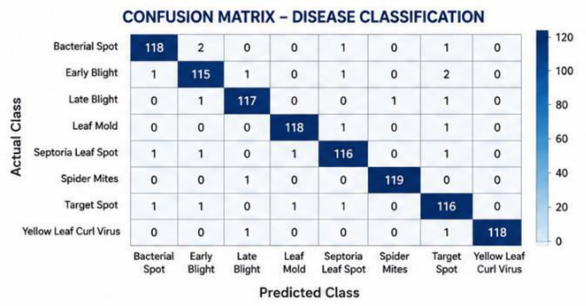

Fig. 3. Confusion matrix for disease classification on the test set.

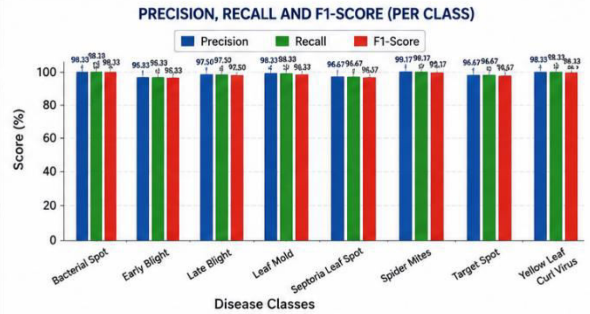

Fig. 4. Precision, recall and F1-score for each disease class.

Overall Performance Summary (Test Set)

Overall Accuracy	Macro Precision	Macro Recall	Macro F1-Score	Weighted F1-Score
97.29%	97.60%	97.60%	97.59%	97.30%

XIII. APPLICATIONS

- Precision Agriculture
- Smart Farming
- Crop Health Monitoring
- Agricultural Advisory Systems
- Mobile Plant Disease Diagnosis
- Disease Prevention Support

XIV. LIMITATIONS

- Performance depends on image quality.
- Field images with complex backgrounds may reduce accuracy.
- Limited dataset diversity may affect model generalization.
- Internet access is required for web deployment.

XV. FUTURE ENHANCEMENTS

Future work includes integrating IoT sensors, mobile application support, cloud deployment, disease severity estimation, multilingual support, and drone-based crop monitoring to improve the scalability and usability of the system.

XVI. CONCLUSION

This paper presented a lightweight MobileNetV3-based multi-task framework for plant leaf disease detection and recommendation. The proposed system accurately identifies plant species and diseases while providing treatment recommendations through a Flask web application. The system offers an efficient, accurate, and scalable solution for precision agriculture and real-time crop disease management.

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