Plant Leaf disease detection

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***Abstract*—Plant diseases caused by pathogens such as bacteria, fungi, and viruses result in significant agricultural losses worldwide, making early detection essential for effective crop management. Recent advances in machine learning and deep learning have enabled automated plant disease detection using leaf images and videos. This study focuses on identifying plant leaf diseases through image and video based analysis. For image classification, a Random Forest machine learning algorithm is employed, while video-based disease detection utilizes the ResNet-50 deep learning model. The proposed approach evaluates performance using metrics such as accuracy, precision, and efficiency. These techniques support timely disease diagnosis, reduce crop losses, and improve yield quality. The system is suitable for practical deployment in agriculture fields, nurseries, and educational gardens, contributing to sustainable farming and food security.**

Keywords Plant disease detection, Random Forest, ResNet-50, Machine Learning, Deep Learning

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I. Introduction

The Global Report on Food Crises(GRFC) 2025 show conflict, economic shocks, climate extremes and forced displacement continued to drive food insecurity and malnutrition around the world, with a catastrophic impact on many already fragile regions. In 2024, more than 295 million people across 53 countries and territories experiences acute levels of hunger. On 12 May-2025 International Day of Plant Health, Food and Agriculture Organization (FAO) estimated that plant pests and diseases destroy nearly 40Traditional machine learning techniques have been used to identify injuries of plant leaves [2]. However, deep learning methods have shown better performance due to their autonomous feature extraction and classification capabilities when applied to leaf images [3] New CNN models, such as VGG-16, VGG-19 [4], Xception [5], Denesenet-201 [6], AlexNet [7], ResNet-50 [8], MobileNet [9], MobileNet-V2 [10] etc., offer powerful tools for automatically learning complex patterns from plant leaf images. These models are typically previously trained on extensive datasets such as ImageNet and are commonly used in two main approaches: training from scratch and transfer learning. In training from scratch, the models are trained entirely on the plant leaf images with randomly initialized weights. While transfer learning involves adapting a pre-trained model to a new, task-specific domain by fine-tuning certain layers. It is a widely adopted strategy due to its efficiency in terms of training time and its ability to perform well with limited data. In this paper, we provide a comprehensive comparative analysis of eight prominent deep learning models: VGG-16, VGG-19, Xception , Denesenet-201 , AlexNet , ResNet-50 , MobileNet, MobileNet-V2 for plant disease classification. We evaluate the model's performance under two learning strategies: transfer learning and learning from scratch. We employ the PlantVillage dataset [7] which contains 54,305 picture samples of various plant disease species. To assess the models under different classification scenarios, the dataset was divided into three primary categories: binary-class plants, multi-class plants, and distinct-class plants. A cross-validation strategy was employed to guarantee a solid and trustworthy performance assessment. This study significantly expands upon previous research by incorporating a wider array of deep learning architectures and systematically evaluating two distinct learning paradigms: transfer learning and training from scratch. Furthermore, we assessed model performance across diverse classification scenarios, including binary and distinct plant disease categorization. This comprehensive experimental design offers a more robust and reliable evaluation of model generalizability and their practical utility in real-world agricultural applications.

II. Ease of Use

A. Abbreviations and Acronyms

AI - Artificial intelligence
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ML - Machine Learning
RF - Random Forest
LG - Logistic Regression
CNN - Convolutional neural network
VGG - Visual Geometry Group
KNN - K Nearest Neighbour
SVM - Support Vector Machine
DCNN - Deep Convolution Neural Network
GLCM - Gray Level Co-occurrence Matrix
ResNet - Residual Network
Xception - Extreme Inception

Identify applicable funding agency here. If none, delete this.

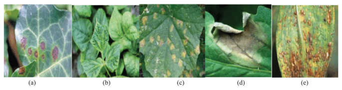

Fig. 1. (a) Bacterial blemish [19] (b) Viral Mosaic [20] (c) Late Blight [22] (d) Early Blight [22] (e) Rust.

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