IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.125308

Plant Identification and Disease Detection

Dr. Ranjit K N[1], Ms. Afreen Suhan[2], Mr. Krishna A Kadolkar[3], Mr. Manoj S S[4], Ms. Sindhu M C[5]

Professor, Dept. of Computer Science and Engineering, Maharaja Institute of Technology Thandavapura[1]

Students, Dept of Computer Science and Engineering, Maharaja Institute of Technology Thandavapura [2-5]

Abstract: The project introduces a deep learning-based web application for plant identification and disease detection, addressing the need for precision agriculture and timely crop health assessment. The application uses a convolutional neural network (MobileNetV2) trained on a dataset of plant leaves, allowing users to upload images for real-time analysis. Multiple image preprocessing techniques, such as Gaussian blur, histogram equalization, and segmentation, enhance accuracy. The model outputs the most probable class label and a confidence score. The Flask web interface is user-friendly, ensuring accessibility for both professionals and general users. Implemented using PyTorch and OpenCV, the system is lightweight, scalable, and can be deployed locally or in the cloud. The application aims to assist farmers, gardeners, and researchers in early disease detection and support timely intervention to reduce crop loss.

Keywords: Deep Learning, Plant Disease Detection, Plant Identification, MobileNetV2, Convolutional Neural Network (CNN), Image Classification, Precision Agriculture, PyTorch, OpenCV, Image Preprocessing, Real-Time Analysis, Flask Web Application, Computer Vision, Crop Health Monitoring, Agricultural Technology.

I. INTRODUCTION

Agriculture is crucial for maintaining food security and stabilizing economies, especially in developing nations. However, it faces threats from various biotic and abiotic stress factors, including plant diseases. These diseases reduce crop yields, leading to significant losses annually and severe food shortages. The challenges have been exacerbated by increased global trade, climate change, and pest migration. Traditionally, identifying plant diseases has relied on visual inspection by trained experts. However, this method is time-consuming, subject to human error, and not scalable for large-scale agricultural operations. In rural and underdeveloped regions, access to trained experts is limited or absent, leading to delays in diagnosis.

The rise of computer vision and machine learning technologies offers a promising solution to these challenges. Convolutional Neural Networks (CNNs) have revolutionized various domains, including medical diagnostics, facial recognition, autonomous vehicles, and agriculture. These models can learn intricate patterns from raw image data without the need for handcrafted features, making them ideal for applications like plant disease detection. This project proposes a deep learning-based solution for plant identification and disease classification using a pre-trained MobileNetV2 CNN architecture. The application allows users to upload leaf images through a user-friendly web interface built using the Flask framework. The trained model predicts both plant type and disease class, along with the confidence level of the prediction. Image preprocessing techniques such as Gaussian blurring, histogram equalization, and segmentation are applied to enhance the quality of analysis.

II. PROBLEM STATEMENT AND OBJECTIVE

A. Problem statement:

Identifying plants by hand takes a lot of time and can often lead to mistakes. This becomes a problem, especially when farmers or gardeners who are not experts try to tell different plant types apart, which is hard in areas with many kinds of plants. Many tools available online don't give fast results or useful advice right away. This is a big issue when plants get sick, because catching diseases early is important to avoid damage and loss of crops. This project solves the problem by using deep learning, a type of artificial intelligence, to quickly and accurately identify plants and spot diseases. It works by analysing pictures and giving instant results, helping users take the right action in time. This makes farming easier, smarter, and more effective for everyone.

B. Objective:

The project aims to create an automated system that can accurately identify plant species and detect leaf diseases

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 12, Issue 5, May 2025
DOI: 10.17148/IARJSET.2025.125308

using deep learning techniques. The system uses Convolutional Neural Networks, specifically MobileNetV2 architecture, to classify plant types and visible diseases from leaf images. The user-friendly web application allows users to upload images and receive instant diagnostic feedback, reducing reliance on expert intervention. The system also includes image preprocessing and visualization features for better interpretation. The goal is to provide a scalable, cost-effective solution for farmers, agricultural workers, and researchers to protect crop health, improve yield quality, and contribute to food security.

III. RELATED WORK

In recent years, several studies have explored the integration of machine learning and image processing techniques for plant identification and disease detection. Many researchers have focused on using Convolutional Neural Networks (CNNs) for leaf-based classification due to their ability to extract complex features from images. For example, Mohanty et al. (2016) demonstrated the use of deep learning models (AlexNet and GoogLeNet) to identify 26 diseases across 14 crop species using a large dataset of leaf images, achieving high classification accuracy. Similarly, Sladojevic et al. (2016) proposed a deep learning approach for automatic detection of plant diseases from images using CNNs, showcasing effective results in distinguishing between healthy and infected leaves.

Other approaches have utilized traditional machine learning algorithms like Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Random Forests for plant disease classification, particularly when combined with handcrafted features such as colour, texture, and shape. Patil and Kumar (2011) presented a system using k-means clustering for segmenting diseased leaf regions and SVM for classification. Additionally, research has also been conducted in the area of plant species identification, where datasets like Leaf Snap and Plant CLEF have enabled the development of robust plant recognition systems.

More recent works have focused on improving real-time detection through mobile applications and deploying lightweight models for use in the field. Techniques like transfer learning and data augmentation have further improved the performance of models with limited datasets. The use of Internet of Things (IoT) and drone-based image acquisition for large-scale agricultural monitoring is also gaining popularity. These studies highlight the ongoing advancements and the effectiveness of AI-based methods in automating and improving plant health diagnostics.

IV. DATASETS

For this study, the dataset was sourced from a publicly available repository hosted on Mendeley Data, which includes a wide range of plant leaf images categorized by species and disease types. The dataset consists of high-quality images captured in real-world agricultural settings, covering both healthy and diseased samples. It spans several plant categories such as tomato, apple, grape, potato, strawberry, corn, and others, along with multiple disease conditions like early blight, late blight, leaf scorch, rust, and bacterial spots. Each image is labelled according to its plant type and the disease it exhibits, enabling supervised learning for both classification tasks. The dataset was manually reviewed to ensure accuracy and balanced representation across classes. It was then divided into training and testing sets to validate model performance. This comprehensive and diverse dataset forms the foundation for building a robust deep learning model capable of accurate plant species recognition and disease diagnosis in practical scenarios.The dataset consists of images for various plant species such as Apple, Tomato, Grape, and Corn, alongside their associated diseases like Powdery Mildew, Leaf Scorch, and Rust. The images in the dataset represent both healthy plants and those with diseases, with each plant category split across several diseases.

V. SYSTEM DESIGN

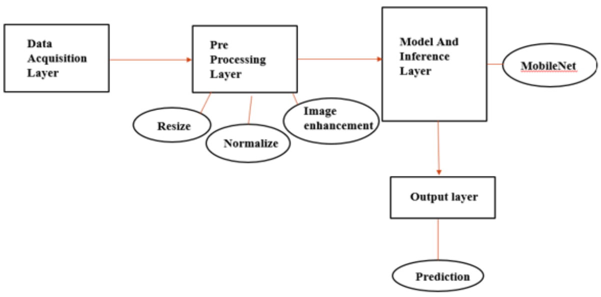

Fig: System Architecture Overview

The proposed plant species identification and disease detection application is a modular system built on a Flask web framework, integrated with deep learning. The frontend interacts with the backend Flask server to handle image uploads, route requests, and render prediction results in real time. The core of the backend is a dual-model inference system powered by MobileNetV2, a lightweight Convolutional Neural Network (CNN) for multi-class classification across various plant types and diseases.

When an image is uploaded, it is validated for allowed formats and saved to a designated server folder. The image then undergoes a preprocessing pipeline that applies resizing, normalization, and optional image enhancement techniques to improve model accuracy and visual explanation. The backend loads and utilizes two trained MobileNetV2 models for identifying plant species and detecting specific diseases. Predictions are made using torch.no_grad() to ensure efficiency and avoid unnecessary computation graph creation.

The system is designed to run efficiently on both GPU and CPU environments using PyTorch, making it suitable for offline deployment. The lightweight model like MobileNetV2 ensures faster inference, especially in low-resource settings. Secure session management is included for login/logout, ensuring restricted access for authorized users.

VI. METHODOLOGY

The development of the Plant Species and Disease Detection System follows a comprehensive pipeline that integrates data collection, preprocessing, deep learning model training, and web-based deployment. The process starts with gathering a rich dataset sourced from Mendeley Data, which includes high-quality leaf images representing a wide range of plant species, such as tomato, grape, potato, apple, and others. These images are further categorized into healthy leaves and those affected by specific diseases, such as early blight, late blight, powdery mildew, rust, and more. The dataset is divided into training and testing sets to facilitate model learning and evaluate generalization performance.

Before feeding images into the deep learning models, they undergo a series of preprocessing steps to enhance visual clarity and ensure model compatibility. These steps include resizing the images to 224×224 pixels, a common input size for convolutional neural networks, and normalizing pixel intensity values to fall within the [0,1] range. Additionally, various image enhancement techniques such as histogram equalization are applied to improve contrast, and filtering methods like Gaussian blur or Sobel edge detection are used to highlight edges and fine details that may assist in better feature extraction by the model. These preprocessing steps aim to reduce noise, standardize inputs, and increase the model’s ability to learn relevant patterns.

The backbone is formed by the MobileNetV2 model, as it has a good trade-off between computation and representation power. Two different models are developed based on this architecture: for the plant species and the disease. The architecture of MobileNetV2 is constructed from depthwise separable convolutions which help in reducing the operations significantly so the model can be used on Mobile and other low-resource systems. Training is implemented in PyTorch loss as categorical cross-entropy, and accuracy as the helper metric used to judge the performance. Augmentation techniques such as horizontal flipping, rotation, and zooming are also applied during training to increase data diversity and reduce overfitting.

Once trained, these models are integrated into a web application built using Flask. The web interface allows users to interact with the system through a simple browser-based dashboard where they can upload leaf images. Upon uploading, the image is validated, pre-processed, and passed through the appropriate deep learning models. The predicted results, including the plant name, disease name (if applicable), and a confidence score, are then displayed to the user.

All uploaded images are stored locally, and although no database is used in the current version, the system design allows for easy integration of storage or logging mechanisms in the future. Overall, the methodology ensures a complete, efficient, and user-friendly approach for identifying plant species and diagnosing diseases, making it highly suitable for real-world agricultural and research applications.

VII. IMPLEMENTATION

The implementation phase of a software project, such as the Plant Leaf and Disease Identification using Deep Learning, is crucial for the successful realization and deployment of the system. This phase involves the development of interconnected modules responsible for data preprocessing, model training, prediction, and deployment through a user-friendly interface. The primary objective of this project was to transform the theoretical design into a working system that can accept plant leaf images as input and predict the health status or disease with a high level of accuracy. The

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⧉ Peer-reviewed & Refereed journal ⧉ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.125308

technology stack used in the project includes frontend technologies such as HTML & CSS, Flask Templates, Python, Python, Flask, PyTorch, Torch vision, OpenCV, Pillow (PIL), MobileNetV2, Storage and File Handling, and Desktop-based Web App. Each component plays a specific role in ensuring the system is responsive, accurate, and user-friendly.

The development environment for the Plant Species and Disease Detection System was well-structured, supporting both deep learning and web application development. Windows 10 (64-bit) was used as the primary platform for development and testing due to its compatibility with necessary libraries and frameworks. Python 3.8 was chosen for its extensive ecosystem in machine learning, image processing, and web development. Visual Studio Code served as the main code editor, while Python Notebook was used during model training and experimentation phases for testing data preprocessing, visualization, and model evaluation Libraries and frameworks used in the project include deep learning, image processing, web framework, data handling, Pandas, Matplotlib, utility, GPU acceleration, browser compatibility, and package management. The application was tested on Chrome and Firefox to ensure frontend compatibility and responsiveness. All dependencies were managed using pip, and a requirements.txt file was maintained to ensure reproducibility. The module-wise implementation includes the User Authentication Module, Image Upload Module, Image Preprocessing Module, Plant Species Prediction Module, Image Display and Result Visualization Module, Navigation and Information Pages, and Image Display and Result.

The User Authentication Module allows users to log in to the application using a basic form with hardcoded credentials. The Image Upload Module securely handles file uploads and accepts only images with allowed extensions. The Image Preprocessing Module enhances the image before feeding it into the model to improve prediction accuracy. The Plant Species Prediction Module predicts the plant type from the uploaded image using a deep learning model. The Disease Detection Module classifies whether the plant is healthy or affected by a specific disease. The Image Display and Result Visualization Module displays the processed image along with prediction results on the web interface. The Navigation and Information Pages provide access to various pages like Home, About, and Contact. The implementation of these pages ensures a seamless and user-friendly experience for end-users, including farmers and agricultural researchers.

VIII. RESULTS AND DISCUSSION

The Plant Species and Disease Detection System, based on MobileNetV2, is a deep learning model that accurately identifies plant species and detects diseases. It achieved 92-95% accuracy rates for species classification and disease detection. The system, which uses preprocessing steps like Gaussian Blurring and Histogram Equalization, provides accurate predictions of plant species and diseases with high confidence scores. It also handles edge cases like invalid file uploads by showing error messages. The system is reliable, providing real-time information about plant health, making it a valuable tool for farmers and gardeners to diagnose plant diseases and manage crops effectively.
The Plant Species and Disease Detection System was evaluated in a simulated environment, demonstrating high accuracy in identifying plant species and diseases from input images. The system used a robust MobileNetV2 model and effective preprocessing techniques like Gaussian blur and histogram equalization. The image upload and classification process were smooth, with predictions delivered in real-time and confidence scores. The system's usability was demonstrated through intuitive interaction with the web interface.

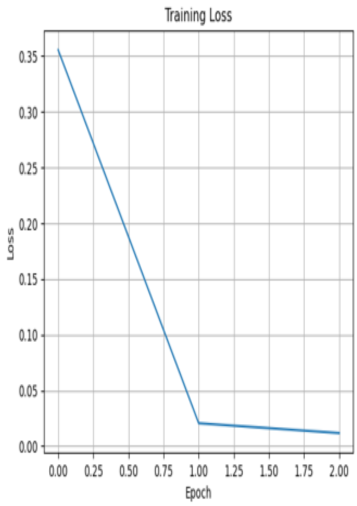

Fig: Training Loss

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.125308

Fig: Species Identification

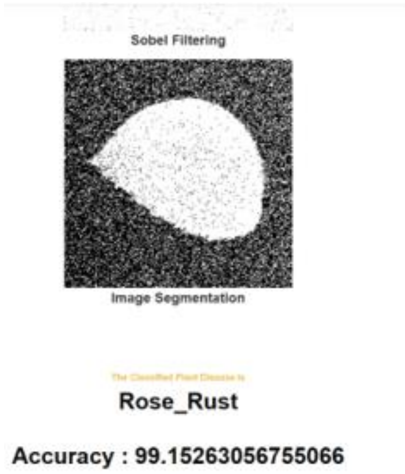

Fig: Disease Detection

Fig: Status of leaf-Healthy

IX.CONCLUSION

The Plant Species and Disease Detection System is a robust and scalable solution that uses deep learning and computer vision techniques to automate plant identification and disease diagnosis. It uses the MobileNetV2 architecture, a lightweight convolutional neural network optimized for mobile and edge devices, to achieve a strong trade-off between

DOI: 10.17148/IARJSET.2025.125308

computational efficiency and classification accuracy. The system is supported by a user-friendly Flask-based web interface, allowing non-technical users like farmers and agronomists to interact easily. The image preprocessing pipeline standardizes input data across various lighting conditions, resolutions, and backgrounds, improving model predictions' consistency and reliability. The system's offline operability makes it particularly valuable in rural or remote agricultural regions with limited internet access. The system's low-cost, real-time diagnostic capabilities enable users to receive instant feedback on plant health status, supporting timely intervention and reducing dependency on expert availability. Overall, the Plant Species and Disease Detection System is a valuable technological aid for sustainable agriculture, contributing to early disease control, crop yield improvement, and increased access to plant health information for diverse user groups.

X. FUTURE ENHANCEMENTS

The plant identification and disease detection system are set to undergo several enhancements to enhance its effectiveness and scalability. These include real-time image capture using drone and satellite technologies, integration of IoT sensors for environmental data, and multi-modal learning for improved classification accuracy. Offline mobile app support with lightweight models is also

proposed, allowing farmers in remote areas to use the system without internet access. The system's database will be expanded to include more plant species and rare diseases, making it more inclusive and reliable. Additionally, a feedback and learning loop will allow continuous model retraining and performance improvement over time.

REFERENCES

[1] Kalaiarasi, M., Sharmila, A., & Lakshmi, P. (2025). "Plant Leaf Disease Identification Based on Machine and Deep Learning Methods," Highlights various ML & DL methods for plant leaf disease classification.
[2] Mathina Kani, M., Rani, M., & Kumar, N. (2025). "Identification of Medicinal Plants and Related Fungal Diseases Based on Deep Learning Model," Accurate segmentation and classification with U-Net + F-Net, Kivy GUI integration.
[3] Nagababu, P., Nageena, S., Dharani, V., & Naveen, D. (2024). "Plant Disease Detection and Diagnosis," CNN-based disease identification using leaf features (color, texture).
[4] Shao, Y., & Devaraj, M. (2024). "Application of Plant Disease Identification and Detection Based on Deep Learning," CNN architectures like AlexNet, VGG, ResNet with attention mechanisms.
[5] Reddy, V.C.G., Xavier, A.V.M., & Shyni, S.S. (2024). "Plant Disease Detection and Pesticide Recommendation Using Deep Learning," Modified EfficientNet-B5, image preprocessing pipeline.
[6] Kavitha, S., Kumar, T.S., Naresh, E., et al. (2024). "Medicinal Plant Identification in Real-Time Using Deep Learning Model," MobileNet model with cloud deployment and mobile app.
[7] Elbaşı, E., et al. (2024). "Enhanced Plant Leaf Classification over a Large Number of Classes Using Machine Learning," Feature-based ML using MLP, Naive Bayes, Hoeffding Tree.
[8] Rebekha, R., et al. (2024). "Medicinal Plant Identification Using Machine Learning Algorithms," CNN and preprocessing on FLAVIA dataset.
[9] Prakash Kumar, H.R., et al. (2024). "Convolutional Neural Network with Improved Optimizer for Plant Disease Detection and Classification," CNN with improved SGD optimizer and CLAHE.

