IJARCCE

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.151150

PLANT DISEASE DETECTION USING DEEP LEARNING AND WEB-BASED APPLICATION

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Abstract: Agriculture plays a crucial role in the economic growth of many developing countries, where crop productivity is often threatened by plant diseases. Early and accurate identification of plant diseases is essential to minimize yield loss and ensure sustainable agricultural practices. However, traditional disease detection methods rely heavily on manual inspection and expert knowledge, which are time-consuming, subjective, and not easily accessible to farmers in rural areas. Recent advancements in artificial intelligence, particularly deep learning, offer effective solutions for automated plant disease diagnosis.

This paper presents a **Plant Disease Detection System** based on deep learning techniques for accurate and automated identification of plant diseases from leaf images. The proposed system employs a **Convolutional Neural Network (CNN)** trained on the Plant Village dataset to classify plant leaves into healthy or diseased categories. The system is implemented as a **web-based application using the Flask framework**, allowing users to upload plant leaf images and obtain instant disease predictions through a simple and user-friendly interface. Image preprocessing and model inference are handled efficiently to ensure reliable performance.

Experimental evaluation demonstrates that the proposed system can accurately identify common plant diseases in a controlled environment, enabling early disease detection and timely preventive measures. The developed solution serves as an effective educational and decision-support platform, highlighting the practical application of artificial intelligence and computer vision in modern agriculture.

Keywords: Plant Disease Detection, Deep Learning, Convolutional Neural Network, Computer Vision, PyTorch, Flask, Agriculture, Image Classification

I. INTRODUCTION

Agriculture is one of the most critical sectors supporting food security and economic stability, particularly in developing countries such as India. Crop productivity is highly dependent on plant health, and plant diseases pose a significant threat by reducing yield, affecting crop quality, and causing substantial economic losses. Timely and accurate identification of plant diseases is essential for effective crop management and sustainable agricultural practices. However, traditional disease detection methods primarily rely on manual inspection and expert knowledge, which are time-consuming, subjective, and often inaccessible to farmers in rural and remote areas.

With the rapid advancement of artificial intelligence, deep learning techniques have emerged as powerful tools for automating complex visual recognition tasks. In agriculture, computer vision–based approaches enable the analysis of plant leaf images to identify disease symptoms that may not be easily detectable through human observation. Among these techniques, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification by automatically learning discriminative features directly from raw image data, eliminating the need for manual feature extraction.

Early detection of plant diseases plays a crucial role in minimizing crop loss and reducing the excessive use of pesticides and fertilizers. Image-based plant disease detection systems using deep learning provide an efficient and scalable solution for identifying diseases at an early stage, allowing farmers to take timely preventive measures. Such automated systems reduce dependency on agricultural experts and enable faster decision-making in real-world farming environments.

This paper proposes a **deep learning–based Plant Disease Detection System** that utilizes a Convolutional Neural Network to accurately classify plant leaf images into healthy or diseased categories. The proposed system is implemented as a **web-based application using the Flask framework**, providing a simple and user-friendly interface for uploading plant leaf images and obtaining instant disease predictions. The primary objective of this work is to demonstrate the

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effective application of artificial intelligence and computer vision techniques in agriculture by developing a practical, accessible, and scalable solution for automated plant disease diagnosis.

1.1 Project Description

This **Plant Disease Detection project** is a web-based intelligent system designed to assist farmers, agricultural practitioners, and researchers in accurately identifying plant diseases using artificial intelligence techniques. The system focuses on automated disease diagnosis through image-based analysis of plant leaves, eliminating the need for manual inspection and expert intervention. By integrating deep learning models with a simple and user-friendly web interface, the system aims to improve the efficiency and reliability of plant disease identification in real-world agricultural environments.

The proposed system employs a **Convolutional Neural Network (CNN)** trained on labeled plant leaf images from the **PlantVillage dataset** to classify plant leaves into healthy or diseased categories. Image preprocessing techniques such as resizing and normalization are applied to ensure compatibility with the deep learning model and improve prediction accuracy. The trained model analyzes visual patterns and disease symptoms present in leaf images and generates accurate disease predictions.

The system is implemented as a **web-based application using the Flask framework**, allowing users to upload plant leaf images and receive instant disease detection results through a browser-based interface. The backend handles image preprocessing, model inference, and result generation, while the frontend provides clear and accessible visualization of prediction outcomes. The modular design of the system allows scalability and easy integration of additional crop types or disease categories in future enhancements.

1.2 Motivation

The motivation for this work arises from the significant challenges faced by farmers due to plant diseases, which are a major cause of reduced crop yield and economic loss in agriculture. In many agricultural regions, especially in developing countries, disease identification is still performed through manual observation or consultation with experts. This approach is time-consuming, subjective, and often impractical for farmers in rural and remote areas where access to agricultural specialists is limited.

Delayed or inaccurate detection of plant diseases can lead to severe crop damage and increased use of chemical pesticides, negatively impacting both crop quality and environmental sustainability. Although several technological solutions for plant disease detection exist, many require expensive equipment, advanced technical knowledge, or controlled laboratory conditions, making them unsuitable for small-scale and resource-limited farmers.

There is a strong need for a **simple, affordable, and intelligent disease detection system** that can provide early and accurate diagnosis using easily accessible tools such as digital images. Advances in artificial intelligence, particularly **deep learning and computer vision**, offer powerful capabilities for analyzing plant leaf images and identifying disease patterns with high accuracy. This project is motivated by the goal of leveraging these technologies to develop a practical, accessible, and automated plant disease detection solution that supports timely decision-making and promotes sustainable agricultural practices.

II. RELATED WORK

Paper [1] examines traditional approaches for plant disease identification based on manual visual inspection and expert knowledge. These methods rely on observing visible symptoms such as leaf discoloration, spots, and texture variations. Although effective in controlled environments, manual disease detection is time-consuming, subjective, and highly dependent on the availability of agricultural experts. Such approaches are impractical for large-scale farming and are often inaccessible to farmers in rural areas.

Paper [2] explores classical image processing techniques for plant disease detection using features such as color, texture, and shape extracted from leaf images. The authors employ methods like thresholding, edge detection, and texture analysis for disease classification. While these approaches offer faster detection than manual methods, their performance is highly sensitive to lighting conditions, background noise, and variations in leaf appearance. Additionally, the reliance on handcrafted features limits their adaptability and accuracy across different crops and disease types.

Paper [3] investigates machine learning–based plant disease classification using models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees. These models utilize manually extracted features from leaf images to classify diseases. Although improved accuracy is achieved compared to rule-based systems, the effectiveness of these methods largely depends on feature quality and domain expertise. Furthermore, such models struggle to generalize when exposed to unseen disease patterns or diverse real-world conditions.

Paper [4] presents a deep learning–based approach for plant disease detection using Convolutional Neural Networks (CNNs). By training CNN models on large-scale plant leaf image datasets, the study demonstrates significant improvements in disease classification accuracy. The automatic feature extraction capability of CNNs eliminates the need for manual feature engineering and enables robust detection of complex disease patterns. However, many proposed systems focus primarily on model performance and lack practical deployment mechanisms for end users.

Paper [5] discusses web-based and mobile agricultural applications developed for plant disease identification. While these systems improve accessibility, several of them rely on static image comparisons or limited rule-based logic rather than fully trained deep learning models. In addition, some applications require high-quality images and do not effectively handle invalid inputs or real-time usage scenarios, reducing their reliability in practical farming environments.

Paper [6] reviews recent advancements in deep learning applications for agriculture and highlights the growing importance of integrated, user-friendly plant disease detection systems. The study emphasizes the need for scalable solutions that combine accurate deep learning models with intuitive interfaces for real-world adoption. This observation motivates the proposed work, which integrates a CNN-based plant disease detection model with a Flask-based web application to provide an efficient, accessible, and automated disease diagnosis system.

III. METHODOLOGY

A. Data Collection and Preprocessing

The proposed system utilizes a publicly available PlantVillage dataset, which contains labeled images of healthy and diseased plant leaves across multiple crop categories. The dataset provides diverse visual samples representing different disease patterns, textures, and color variations. These images serve as the primary input for training and evaluating the deep learning model.

Prior to model training, the collected leaf images undergo a series of preprocessing steps to ensure consistency and improve classification performance. Each image is resized to a fixed resolution compatible with the Convolutional Neural Network (CNN) input layer. Pixel values are normalized to standardize the data distribution and enhance model convergence. Image preprocessing techniques such as noise reduction and format standardization are applied to reduce unwanted variations caused by lighting conditions or background interference. These steps help the model focus on relevant disease-related features present in the leaf images.

B. Deep Learning Model Architecture

The core of the proposed plant disease detection system is a Convolutional Neural Network (CNN) designed for image-based classification. CNNs are well suited for visual recognition tasks due to their ability to automatically learn spatial features such as edges, textures, and complex patterns from raw image data.

The CNN architecture consists of multiple convolutional layers followed by activation functions, batch normalization, and max-pooling layers to extract hierarchical features from plant leaf images. These layers are followed by fully connected layers that perform classification into predefined disease categories. Dropout layers are included to reduce overfitting and improve generalization. The model is trained using labeled leaf images and optimized to accurately distinguish between healthy and diseased plants.

C. Plant Disease Detection Module

The plant disease detection module performs automated classification of plant leaf images using the trained CNN model. Users upload a leaf image through the web interface, which is then forwarded to the backend for processing. The uploaded image is preprocessed and passed to the CNN model for inference.

The model analyzes visual symptoms such as discoloration, spots, and texture irregularities to identify disease patterns. Based on the learned features, the system classifies the image into one of the predefined disease categories or identifies it as healthy. The predicted disease result is returned along with descriptive information, enabling early disease detection and timely preventive measures.

D. System Integration and Deployment

The complete plant disease detection system is implemented as a web-based application using the Flask framework. The system follows a modular client–server architecture, where the frontend handles user interaction and image upload, and the backend manages image preprocessing, model inference, and result generation.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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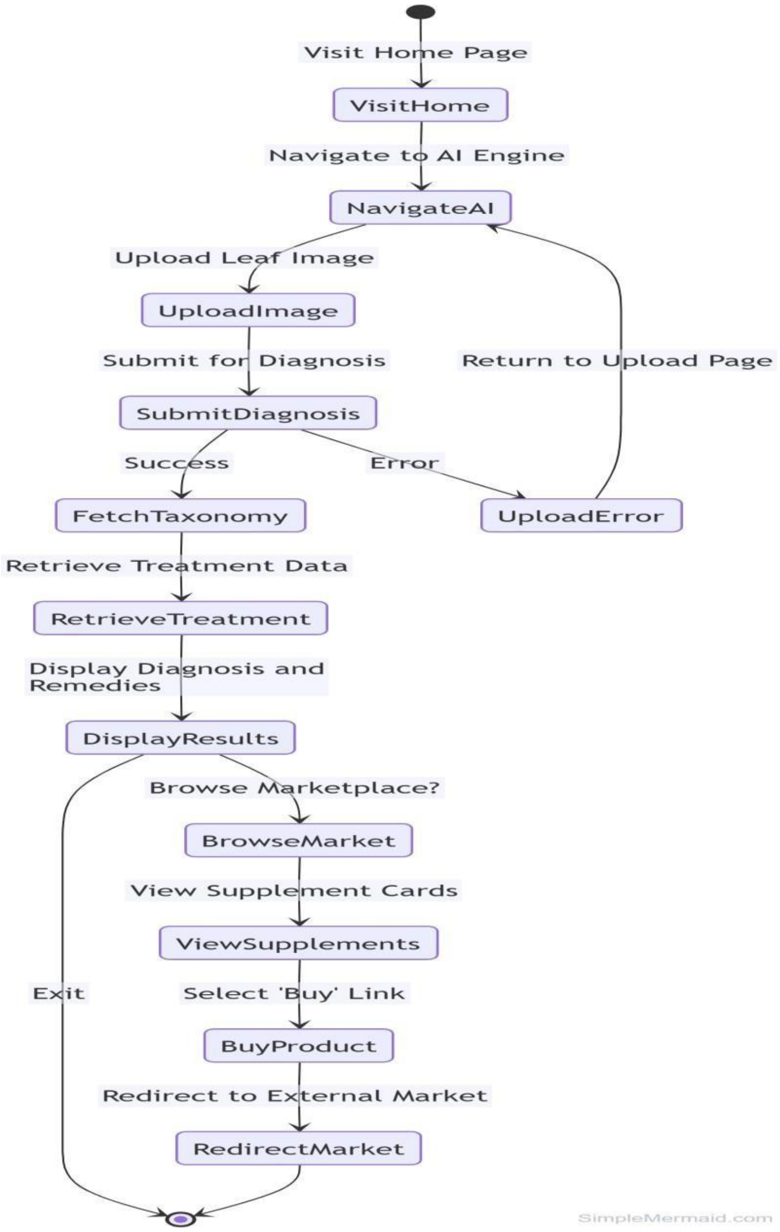
The trained CNN model, implemented using the PyTorch framework, is loaded during runtime to perform efficient and consistent predictions without retraining. The final output is displayed through a simple and user-friendly interface, allowing users to view disease prediction results instantly. The modular design ensures scalability and enables easy integration of additional crop types or disease categories in future enhancements.



E. Hardware and Software Requirements

Hardware Requirements

• **Processor:** A standard multi-core processor such as Intel Core i3/i5 or an equivalent AMD processor is sufficient to execute the web application and perform deep learning model inference efficiently.

• **Random Access Memory (RAM):** A minimum of 4 GB RAM is required for basic execution, while 8 GB RAM is recommended to ensure smoother image processing and model inference operations.

• **Storage:** At least 256 GB of hard disk or solid-state drive (SSD) storage is required to store the dataset, trained deep learning models, and application files.

• **Internet Connectivity:** A stable internet connection is required for downloading datasets, installing dependencies, and accessing documentation or updates during development and deployment.

• **Input and Output Devices:** Standard input devices such as a keyboard and mouse are required. A digital camera or smartphone camera is necessary for capturing plant leaf images used in disease detection.

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Software Requirements

• **Operating System:** The system can be executed on Windows 10/11, Linux, or macOS operating systems, providing flexibility across different platforms.

• **Programming Language:** Python (version 3.8 or higher) is used for implementing the deep learning model and backend logic of the application.

• **Deep Learning Framework:** PyTorch is used to design, train, and deploy the Convolutional Neural Network for plant disease classification.

• **Image Processing Libraries:** OpenCV, NumPy, and PIL are used for image preprocessing tasks such as resizing, normalization, and noise reduction.

• **Web Framework:** Flask is used to develop the web-based application, manage server-side operations, and handle image uploads and prediction requests.

• **Development Tools:** Visual Studio Code (VS Code) and Jupyter Notebook are used for model development, experimentation, and debugging.

• **Database (Optional):** SQLite can be used for lightweight data storage if user authentication or prediction history is required in extended versions of the system.

• **Web Browser:** Google Chrome, Mozilla Firefox, or Microsoft Edge is required for accessing and testing the web application interface.

IV. IMPLEMENTATION AND EVALUATION FRAMEWORK

A. Experimental Setup

The Plant Disease Detection system was developed and evaluated in a local development environment to validate its performance and usability. The experimental setup used for implementation and testing is summarized as follows:

• **Hardware:** Intel Core i5 processor with 8 GB RAM, sufficient for image preprocessing and deep learning model inference.

• **Software:** Visual Studio Code as the primary development environment, Python 3.8 or higher, Flask framework for web application development, and required deep learning and image processing libraries.

• **Tools and Frameworks:** PyTorch for implementing and deploying the Convolutional Neural Network, OpenCV and PIL for image preprocessing, and NumPy and Pandas for numerical operations and data handling.

• **Network:** A standard broadband internet connection was used for downloading datasets, installing dependencies, and testing web-based image upload functionality.

The system was tested using plant leaf images from the PlantVillage dataset under controlled conditions.

B. Feature Implementation

• **Plant Disease Detection Module:**
The core functionality of the system is the plant disease detection module, which allows users to upload plant leaf images through the web interface. Uploaded images undergo preprocessing, including resizing and normalization, before being passed to the trained CNN model. The model classifies the image into healthy or diseased categories and identifies the specific disease class.

• **Deep Learning Model Integration:**
A trained Convolutional Neural Network implemented using PyTorch is loaded at runtime to perform image classification. The model automatically extracts visual features from leaf images and generates accurate predictions without manual feature engineering.

• **Web Application and User Interaction:**
The system is deployed as a web-based application using the Flask framework. The frontend provides a simple and intuitive interface for image upload and result visualization. Prediction results, including disease name and descriptive information, are displayed clearly to the user.

• **Input Validation and Error Handling:**
The system includes validation mechanisms to ensure that only valid image files are processed. Invalid or unsupported inputs are handled gracefully with appropriate error messages, ensuring system stability and reliability.

C. Evaluation Methodology

The proposed system was evaluated based on the following key performance criteria:

1. **Accuracy:** The accuracy of the CNN model in identifying plant diseases from leaf images was evaluated using test samples from the dataset.

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2. **Usability:** Usability testing was conducted to verify that users with minimal technical knowledge could easily upload images and understand the prediction results without external assistance.
3. **Reliability:** The system was tested under different input scenarios, including repeated image uploads and invalid inputs, to assess stability and error-handling capability during continuous usage.

D. Results and Observations

The experimental evaluation demonstrates the effectiveness of the proposed Plant Disease Detection system:

• **Disease Classification Accuracy**: The CNN-based model successfully identified common plant diseases from uploaded leaf images, validating the effectiveness of deep learning for image-based disease detection.

• **Early Disease Identification:** The system enabled early detection of plant diseases, allowing timely preventive action and reducing potential crop loss.

• **User Experience:** The web-based interface provided a smooth and accessible user experience, allowing quick image uploads and instant display of results.

• **System Stability:** During testing, the application operated reliably without significant delays, even when multiple images were uploaded consecutively, confirming its suitability as a proof-of-concept plant disease detection solution.

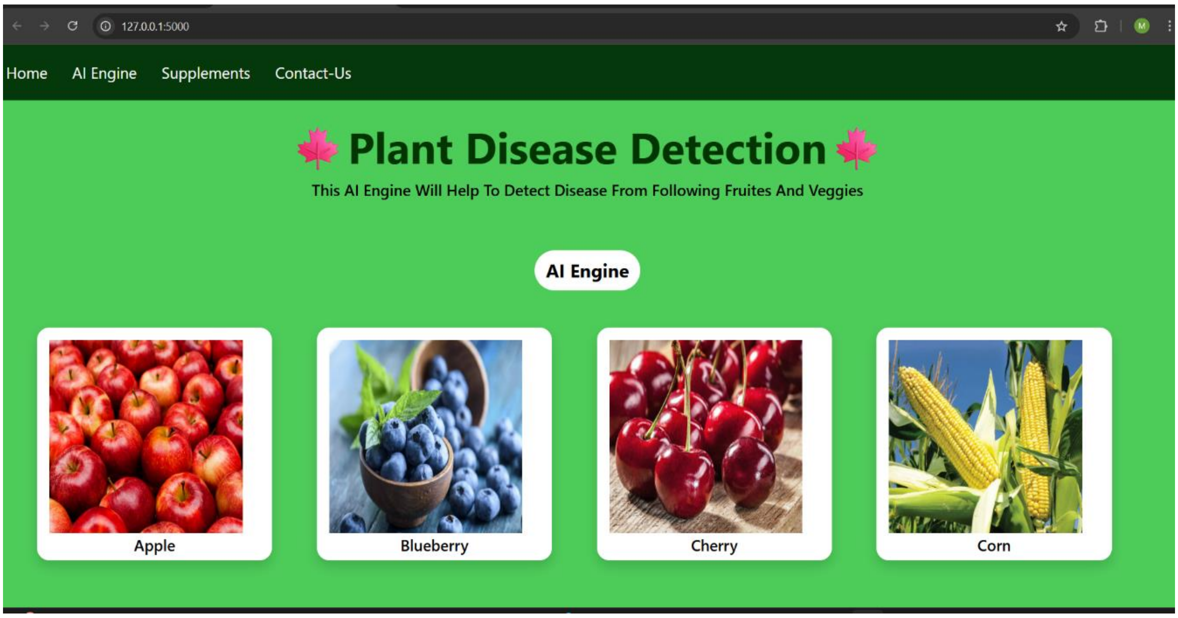

Fig 1. Home Page

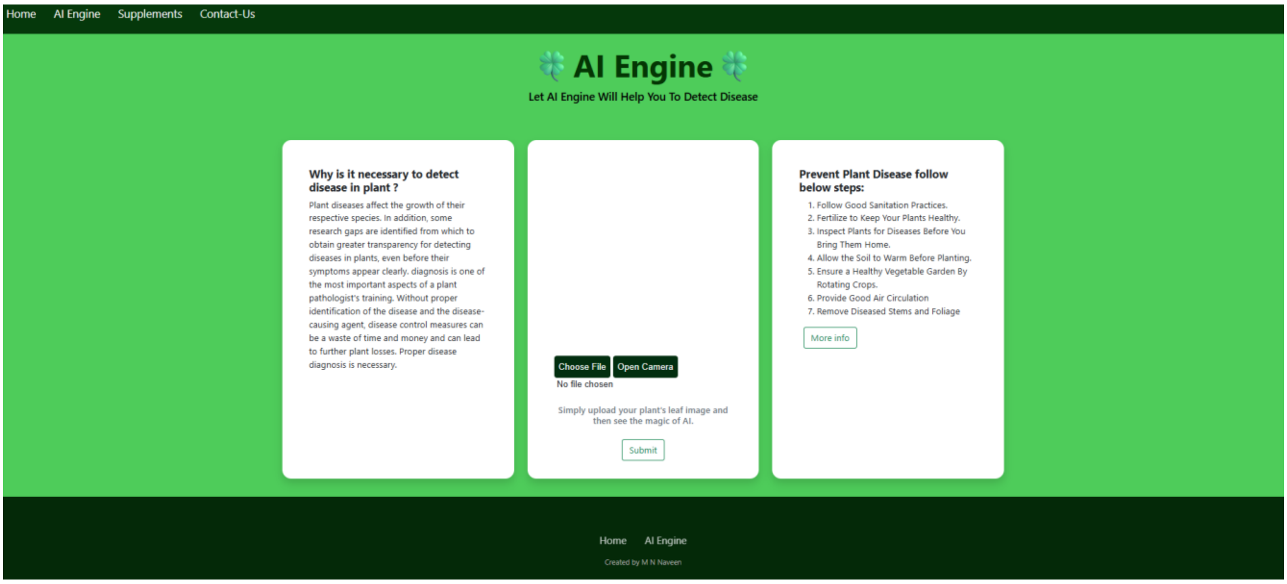

Fig 2. AI Engine

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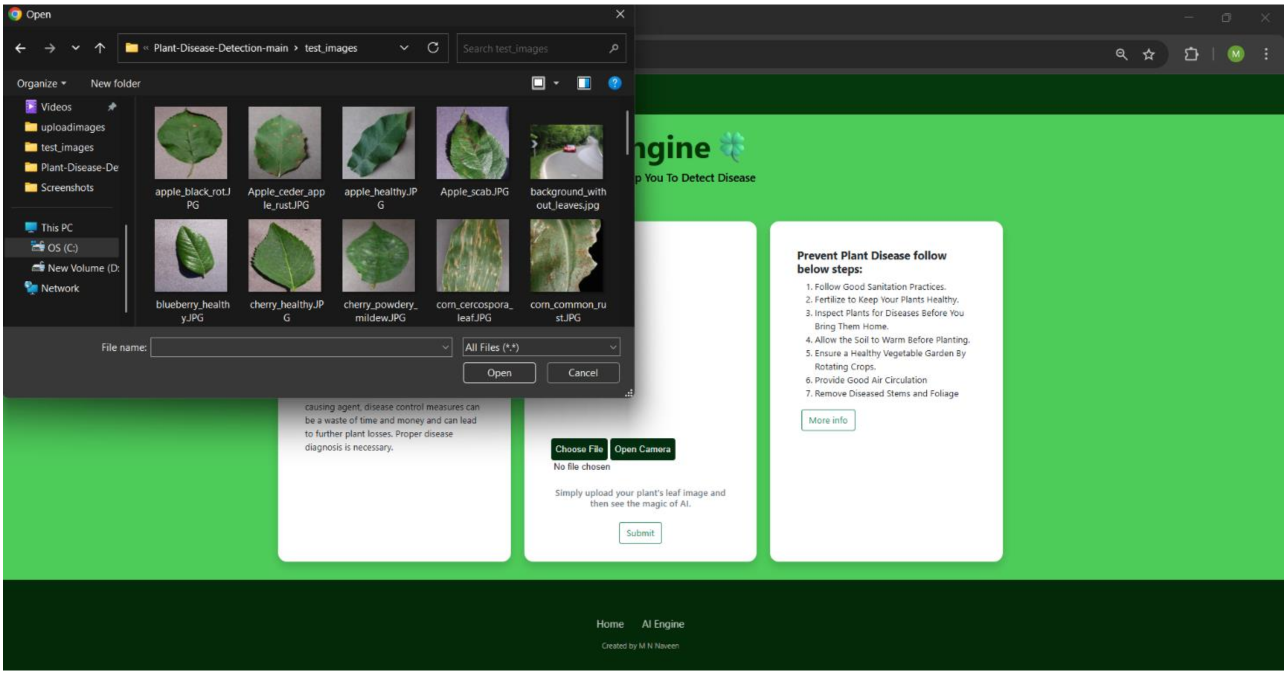

Fig 3. Selecting image

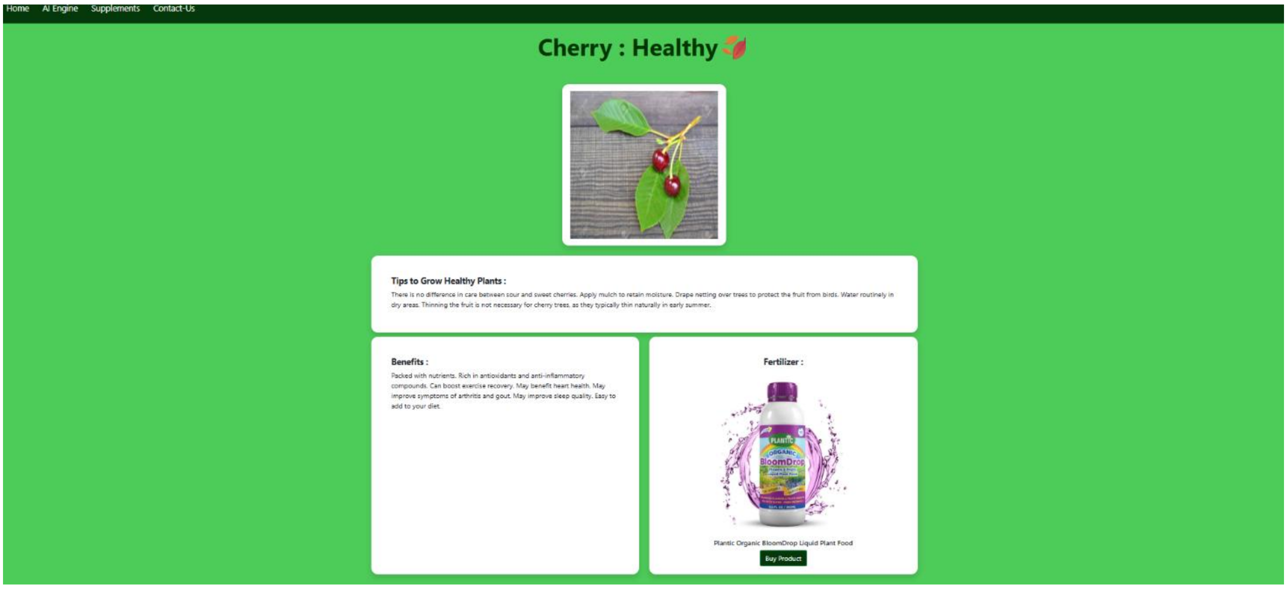

Fig 4. Disease Detection And Supplement

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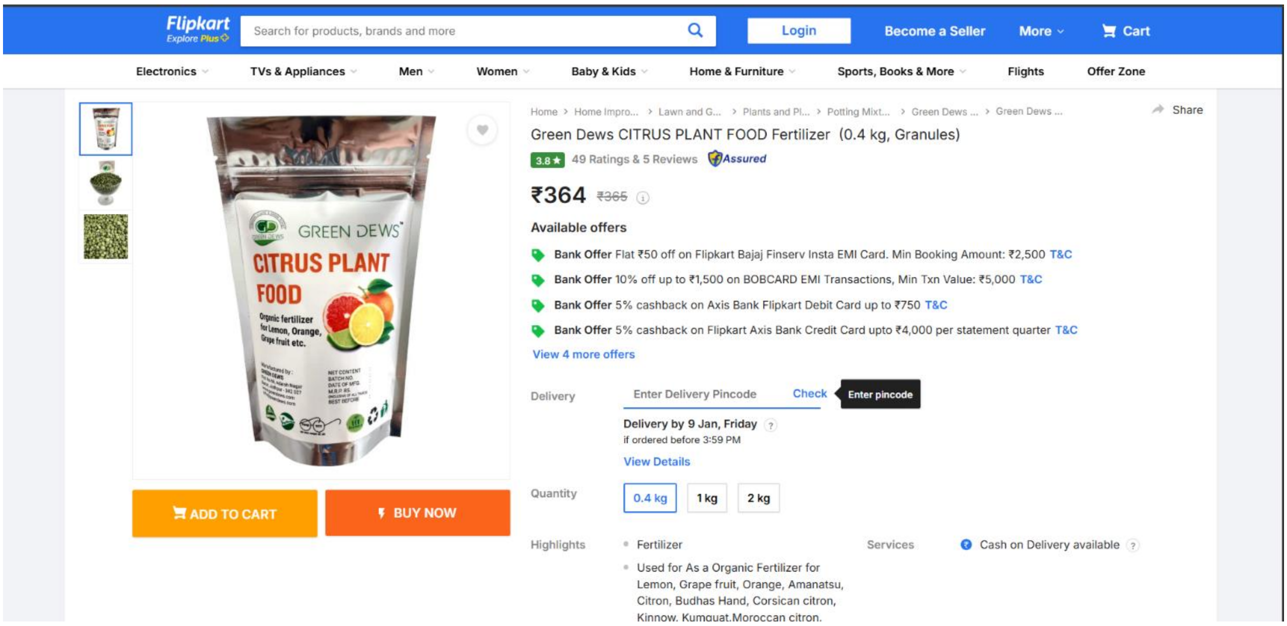

Fig 5. Buy Supplement

V. RESULTS AND DISCUSSION

Performance Analysis

The experimental evaluation confirms the effectiveness and reliability of the proposed Plant Disease Detection system. The web-based architecture enabled smooth interaction between the user interface and the deep learning backend without noticeable delays. Image upload, preprocessing, and disease prediction were performed efficiently, providing near real-time responses to user inputs. The integration of a Convolutional Neural Network with a Flask-based web application ensured seamless communication between system components and stable operational performance.

The system demonstrated consistent behavior across multiple test cases, validating the suitability of the selected deep learning architecture and implementation approach. The modular design also facilitated efficient handling of repeated image uploads and inference operations without system degradation.

Prediction Accuracy and System Reliability

The CNN-based plant disease detection module successfully identified common plant diseases from uploaded leaf images under normal lighting and background conditions. The model effectively learned visual disease patterns such as discoloration, spots, and texture irregularities, resulting in accurate disease classification.

Input validation mechanisms handled invalid image formats and incorrect uploads gracefully, preventing system crashes and maintaining application stability. The system remained reliable during continuous usage and repeated predictions, confirming its robustness as a proof-of-concept solution. Overall, the experimental results demonstrate that the proposed system performs effectively in a controlled environment and highlights the practical application of deep learning and computer vision techniques for automated plant disease diagnosis.

VI. CONCLUSION

This paper presented a **deep learning–based Plant Disease Detection system** designed to provide an automated and accurate solution for identifying plant diseases using image-based analysis. The proposed system effectively integrates a Convolutional Neural Network with a web-based application to classify plant leaf images into healthy or diseased categories. By utilizing deep learning techniques, the system eliminates the need for manual inspection and expert intervention, enabling faster and more reliable disease diagnosis.

The implementation of a **user-friendly web interface** allows users to upload plant leaf images and obtain instant prediction results with minimal technical effort. The integration of image preprocessing and CNN-based inference ensures consistent performance and reliable disease classification. Experimental evaluation demonstrates that the system operates efficiently in a controlled environment and produces accurate predictions across multiple test cases.

International Journal of Advanced Research in Computer and Communication Engineering
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Overall, the proposed Plant Disease Detection framework establishes a **scalable and flexible foundation** for automated disease diagnosis in agriculture. The results highlight the potential of artificial intelligence and computer vision techniques in improving agricultural practices by enabling early disease detection, reducing crop loss, and supporting informed decision-making.

VII. FUTURE WORK

The proposed **Plant Disease Detection system** can be further enhanced in several ways to improve accuracy, scalability, and real-world applicability. Future work may involve incorporating larger and more diverse real-world plant disease datasets to improve model generalization under varying environmental conditions such as lighting, background complexity, and leaf orientation.

Advanced deep learning architectures such as **ResNet, DenseNet, or EfficientNet** can beexplored to enhance disease classification performance. The system can also be extended to support a wider range of crops and disease categories, making it more useful across different agricultural regions. Integration of real-time image capture through mobile devices can enable instant disease detection directly in the field.

Additionally, deploying the system on **cloud platforms** can improve scalability and availability for a larger user base. Future versions may include mobile application support and multilingual interfaces to improve accessibility for farmers with limited technical knowledge. These enhancements can transform the proposed solution into a comprehensive and practical plant disease diagnosis platform for real-world agricultural applications.

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