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Plant Disease Detection Using Image Processing and Deep Learning Techniques

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Abstract— The Plant Disease Detection System is an AI-powered solution designed to help farmers and gardeners quickly and accurately recognize plant health issues. It is built using a custom deep learning model developed in PyTorch that applies Convolutional Neural Networks (CNN) to classify 39 categories of plant diseases across multiple crops using leaf images. The model processes 224×224 RGB images and learns meaningful patterns through a four-layer convolutional architecture integrated with batch normalization to enhance accuracy and stability. For user accessibility, a Flask-based web application is implemented, allowing users to upload plant leaf images that are preprocessed and analyzed by the model to generate real-time predictions. The system also provides detailed information about identified diseases through curated datasets, including their causes, preventive steps, and treatment methods. In addition, the application includes a marketplace feature that offers links to recommended fertilizers and remedies for easy purchase. This integrated AI-based platform not only detects plant diseases but also supports users with actionable solutions, making it a comprehensive agricultural assistance system.

Keywords-Deep Learning, Plant Disease Detection, Convolutional Neural Network (CNN), PyTorch, Flask Web Application, Image Classification, Agriculture AI, Leaf Diagnosis, Treatment Recommendation System

I. INTRODUCTION

The effects of plant disease on worldwide food supply are severe, contributing to crop yield loss and economic hardship for farmers. The primary method for identifying plant disease traditionally has been the manual inspection of plant material by trained experts, which is a time-consuming, subjective process often not available to rural communities. However, with advances in artificial intelligence (AI), especially the use of Convolutional Neural Networks (CNN) for image-based classification, there has been great success with the application of these techniques to identify plant disease.

The objective of this project is to create a reliable, rapid, and user-friendly AI system that can effectively identify multiple plant diseases in different types of crops. The system will implement a CNN model (built on PyTorch) to categorize 39 distinct plant diseases into their respective classes, and it will be made available via a Flask web application. Providing users with instant predictions represents a way for farmers to leverage the advantages of modern AI technology in order to address practical agricultural challenges.

The goals of this project are creating a strong deep learning model, providing easy to use web interface for image uploads, providing detailed information on plant disease, providing recommendations for prevention and treatment of plant disease, and supporting farmers by providing a marketplace for supplements (e.g., fertilizers and other treatments) that match the diagnosis of plant disease. The combination of all these features will give the user both a diagnosis and an actionable recommendation to improve crop protection.

By providing farmers with an early indication of crop disease through the use of technology to support expert diagnosis as well as the ability to have a reliable, early detection method for identifying plant disease will assist the farmer in safeguarding himself from potential crop loss. As such, this model was built using the Plant Village dataset, which includes high-quality annotated images, to get the best performance for the model. The CNN architecture incorporates several convolutional layers, batch normalization, as well as appropriate image preprocessing techniques like resizing and normalization. Together, these component selections have enhanced the feature extraction process and provided greater overall accuracy for the model. In addition, the overall end-to-end pipeline of preprocessing through the end prediction and recommendation process is designed to ensure consistency and reliable results for application in the real-world agricultural setting.

II. RELATED WORKS

Shafay et al. (2025), on the other hand, conducted an extensive review to highlight recent advances within plant disease detection technologies by focusing on major challenges like dataset imbalance, environmental noise, and model generalization of systems using AI-based image analysis. In addition, the work tried to discuss gaps to be improved toward obtaining reliable agricultural diagnostics and provided a foundation for modern deep learning systems in precision farming [1].

The paper by Upadhyay et al. (2025) focused on the review of deep learning and computer vision methods used for plant disease detection and included the concepts related to CNNs, transfer learning, and advanced architectures. Their study discussed emerging trends of precision agriculture and revisited how new models outperform traditional machine learning techniques significantly in accuracy and scalability [2].

(3) Wang et al. (2025) explored the application of non-destructive technology in plant diseases identification, focusing on hyperspectral imaging, thermal imaging, and advanced vision-based systems. The results indicated that combination with non-invasive sensing technologies

improves early detection of plant stress and reduces diagnostic errors under practical farm conditions [3].

(4) Miao et al. (2025), on the other hand, presented SerpensGate-YOLOv8, an advanced architecture configuration of YOLOv8 that was optimized for plant disease detection. Accordingly, their model improved accuracy by multiscale feature extraction and attention mechanism and achieved very good scores regarding the identification of weak symptom identification in complicated images of leaves [4].

Duhan et al., 2025, hence proposed a lightweight deep learning model for mobile devices to classify plant diseases efficiently. They were able to show that such optimized architectures compete for accuracy while consuming a lot fewer computational resources and thus are able to make detection feasible for farmers in areas where computing facilities may be limited.

Bouacida et al. developed a generalized deep learning framework that can perform cross-crop disease detection, as presented by the authors in 2025. The method was able to learn robust and transferable features from different datasets, enabling a single model to detect diseases across various plant species, which helps solve scalability issues compared to crop-specific models [6].

7 Ali et al. studied the application of Vision Transformers to plant disease recognition. Among their results, it emerged that ViTs improve over CNNs in modeling long-range interactions across an image, which is relevant for detecting dispersed, or complicated symptoms of disease on plant leaves.

Wang et al. developed a novel, improved multiscale YOLO-based architecture with the goal of better detection accuracy and speed. Novel feature fusion and the use of multi-layer attention improved performance on high-resolution plant disease datasets, thus enabling faster and more precise field diagnoses [8].

(9) Bukhamsin et al. (2025) presented some early, high-throughput plant disease diagnostic strategies based on sensor, imaging tool, and automated learning integration. Their work emphasized early detection as the mainstay to avoid massive crop damage and underlined the great potential of deep learning in automated plant monitoring [9].

(10) Khalid and Talukder [10], in the year 2025, had proposed a hybrid deep multistacking integrated model with the combination of several CNN architectures that enhanced various phases of plant diseases recognition. Their approach strengthened feature diversity and increased classification accuracy, especially for visually similar disease categories.

(11) Kaur et al. (2025) developed YOLO-LeafNet, an enhanced multispecies plant disease detection framework robust to environmental conditions utilizing various data augmentation techniques. Their model showed a high degree of precision under the variation in environmental conditions and proved that augmented datasets play a very significant role in enhancing deep learning's robustness [11].

(12) Ouamane et al. (2025) performed the optimization of the architectures of Vision Transformers to obtain the best performance in plant disease detection. In their work, the methods improved computational efficiency with the minimum loss of accuracy, thus proving the possibility to adapt transformer-based models for specific agricultural image analyses [12].

(13) Ashurov et al. (2025) proposed a depthwise CNN with squeeze-and-excitation modules and residual skip connections. Their network architecture improved feature refinement and smoothed the flow of gradients, thereby enhancing recognition performance for intricate plant disease patterns in images under conditions of variable illumination [13].

In [14], a review on automated plant disease detection has been carried out through Khan et al. in the year 2025. Their explanation defined why the AI-based solution is needed. The limitation related to dataset quality, environmental variation, and interpretability of the model was discussed sequentially. This gave the guideline for their future research focused on resilient and interpretable AI models. (15) Hari and Singh (2025) investigated federated deep learning for plant disease detection to facilitate knowledge sharing without explicit consideration of sensitive or large datasets. Their approach improved generalization across geographically diverse environments while maintaining data privacy and security [15].

III. COMPARISON WITH PREVIOUS METHODOLOGY

Traditional approaches to detect plant diseases relied on traditional machine learning techniques like Support Vector Machines (SVMs), K-Nearest Neighbors (KNNs) and Random Forest Classifiers. The development of these techniques required the expert's feature extraction process to include characteristics such as colour, texture and shape. Although effective in a small controlled dataset, they were not capable of providing accurate results in their comparison against varying light conditions, background noise, leaf orientations, and agricultural realities. The level of accuracy achieved with these methods was dependent upon the quality of preprocessing and the skills of a feature engineer. Therefore, scaling these techniques and performing robust multi-class plant disease classification have been very difficult.

In contrast, the proposed methodology utilises deep learning to overcome all of the issues associated with the traditional method of using handcrafted features for plant disease classification. A Convolutional Neural Network (CNN) automatically creates learned features through a process known as Convolution, and does not rely upon features that have been hand-crafted. This enables the CNN model to be more accurate and able to adapt to changes in the input through learned feature representation. The use of advanced techniques such as batch normalisation, additional convolutional layers, and extensive data preprocessing combine to create a higher level of performance. Additionally, the system will not only classify plant diseases, but also provide information about the disease, preventive actions and supplements by way of a web interface. The system will therefore represent a complete end to end solution for the agricultural industry.

Table 1 – Comparison Table

Aspect	Previous Methods	Proposed Method
Features	Manual	Automatic
Accuracy	Low–Moderate	High
Robustness	Weak	Strong
Scalability	Limited	Broad
Interface	Offline	Web-Based
Output	Classification	Full Guidance
Preprocessing	Heavy	Streamlined
Generalization	Poor	Good
Dataset Handling	Small	Large
Real-World Use	Restricted	Practical

IV. PROPOSED FRAMEWORK

Algorithm Details -

1. Image Preprocessing Algorithm

- Load the input leaf image.
- Resize the image to 224 × 224 pixels.
- Convert the image to RGB format.
- Transform it into a numerical array.
- Normalize pixel values to the range 0–1.
- Convert the array into a PyTorch tensor.
- Add batch dimension for model compatibility.

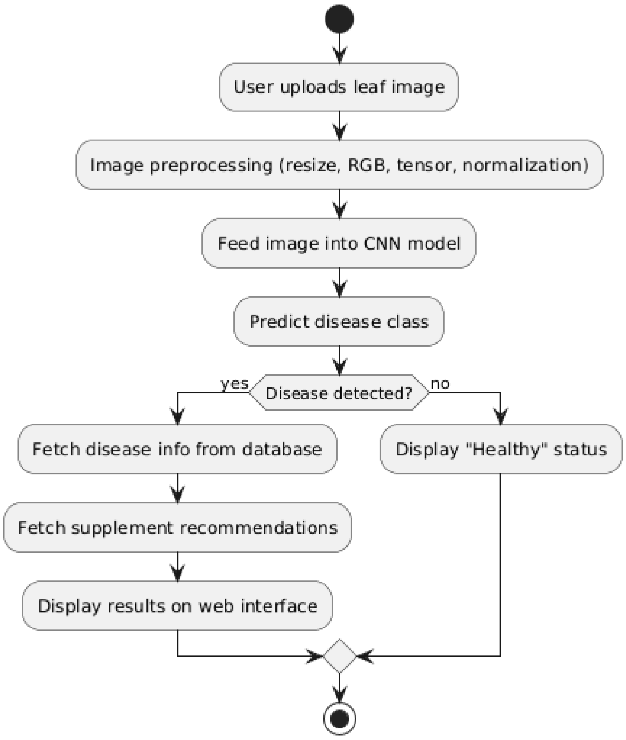


Fig.1.Overall System Workflow

2. CNN Feature Extraction Algorithm

- Pass input through Conv Layer 1 (32 filters) + ReLU + BatchNorm + MaxPool.
- Pass output through Conv Layer 2 (64 filters) + ReLU + BatchNorm + MaxPool.
- Continue through Conv Layer 3 (128 filters) with activation and pooling.
- Pass through Conv Layer 4 (256 filters) with activation and pooling.
- Flatten extracted feature maps into a 1D vector.

3. Classification Algorithm

- Forward the flattened vector into Fully Connected Layer 1.
- Apply ReLU activation.
- Pass output to Fully Connected Layer 2 for 39-class prediction.
- Apply Softmax to convert scores into probability values.
- Select the class with the highest probability.

4. Disease Information Retrieval Algorithm

- Read predicted class label (e.g., "Tomato Blight").
- Search disease_info.csv.

- Fetch details such as description, symptoms, prevention, and treatment steps.
- Display the result on the web interface.

5. Supplement Recommendation Algorithm

- Use predicted disease name.
- Query supplement_info.csv for matching entries.
- Retrieve relevant fertilizers or remedies.
- Display name, usage, and purchase link to the user.

V. DATASET DETAILS

With a vast publicly available library comprising of 61,486 color photos of plant's leaves labelled into 39 categories that include images of healthy plants and images with diseases, this dataset is an excellent source of data to use when training a deep learning model because they were taken using controlled lighting with plain backgrounds. The large amount of data in this dataset also covers numerous different types of plants and diseases, which enables researchers to accurately identify and diagnose a plant disease. Therefore, this dataset is extensively employed in research involving computer vision and agriculture to create automated methods for detecting plant disease using CNNs and other machine learning approaches.

Table 2 – Dataset Details

Aspect	**Description**	**Values / Notes**
Dataset Name	Plant Village Dataset	Widely used for plant disease detection
Total Images	61,486	Includes healthy & diseased leaves
Number of Classes	39 classes	Different plant species & diseases
Image Type	RGB Leaf Images	Color photos of plant leaves
Sources	PlantVillage Project	Academic dataset for agriculture AI
Augmentation Applied	6 Techniques	Flipping, Rotation, Scaling, Gamma Correction, Noise Injection, PCA Color Augmentation
Purpose	Plant Disease Classification	Deep Learning (CNN) Model Training
Dataset Distribution (as used in project)	Train / Validation / Test	36,584 (Train), 15,679 (Validation), Remaining for Test
Folder Structure (ImageFolder)	Class-wise Folders	One folder per plant disease class
Common Image Size (after transform)	224 × 224	Resized for CNN input

VI. IMPLEMENTATION

Stage 1 - Data Preparation

The PlantVillage dataset consists of labeled photographic data for 39 different types of crop diseases. The images are grouped into corresponding directories for training and testing purposes. All images in this data set are standardized to a size of 224 × 224 pixels so that their dimensions remain constant when they are input into the trained model. The dataset will be divided into training and testing datasets, which allows for greater accuracy of performance testing.

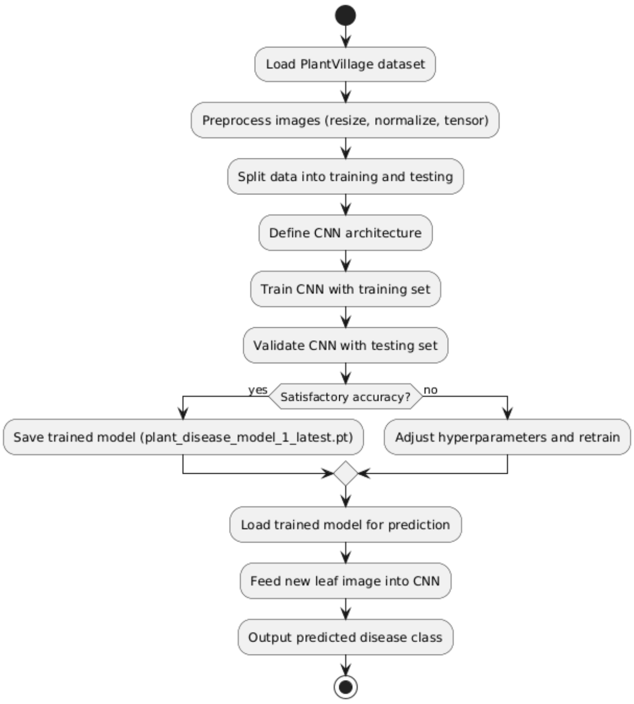


Fig.2.CNN Model Training and Prediction

Stage 2 - Image Preprocessing

All incoming images will be routed through an image preprocessing pipeline before being sent to the connected CNN. The first stage involves converting the image(s) from the original format(s) to RGB format; resizing the image(s) to 224 × 224 pixels; normalizing the color(s) and converting them into tensors. Normalization will stabilize the training process by reducing internal fluctuations; converting the image(s) into tensors will allow easy interactions between

PyTorch and the inputs of the neural network. This process will yield input data that has fewer variances than unprocessed input data, resulting in reduced noise and improved prediction accuracy.

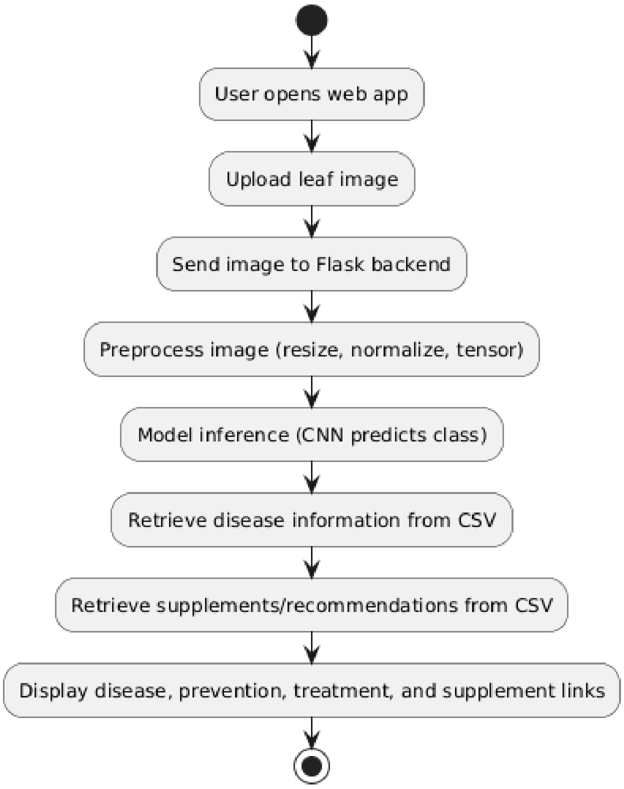


Fig.3.Web Interface and Recommendation

Stage 3 - CNN Model Creation

The model will consist of one custom-built Convolutional Neural Network (CNN) that contains four separate convolutional blocks that have various filter sizes. The filter sizes will start from 32 filters and increase to 64, then 128, and Lastly,256. Each block also includes batch normalization in addition to ReLU activation, both of which are designed to assist with extracting the most relevant features from the images and to assist with providing stable training functions. Additionally, after each convolutional layer, there will be max pooling, which when used along with the convolutional layers, will help reduce the dimensionality of the input images or visuals, while still retaining their most important features.

During Step 4 of building a web-based plant disease diagnostic tool, finally we create the Flask (Python) web app that utilizes the trained CNN model. While building the Flask web app, we also created processes to upload images, process images through the application and send images into the CNN for prediction.

In Step 5 of the process, the application uses the disease image results returned from the CNN model in Step 4, retrieves disease information from disease_info.csv and retrieves suggestions from supplement_info.csv. By making this information available, users will have access to more than just the disease prediction, but also have access to information about the disease, preventative measures, and recommended solutions to help treat the disease.

Step 6 completes the process by designing and deploying a user interface that allows users to upload images of leaves and to view predictions and suggested solutions or treatments. The interface is built using a combination of HTML, CSS, and Flask templates. The web app can be used on multiple devices, allowing farmers and others to effectively diagnose plant diseases, while also providing helpful suggestions on solutions.

VII. RESULTS AND DISCUSSION

A deep learning–based CNN model was effectively designed and evaluated to classify 39 categories of plant diseases across different crops, demonstrating reliable performance during testing. The model's accuracy was largely influenced by the diversity and quality of the dataset used for training, ensuring better generalization across disease classes.

Fig..Home Page

The home interface presents a clean and user-friendly layout where users can easily navigate through different crop categories such as apple, blueberry, cherry, and corn to begin the detection process

Why is it necessary to detect disease in plant ?

Plant diseases affect the growth of their respective species. In addition, some research gaps are identified from which to obtain greater transparency for detecting diseases in plants, even before their symptoms appear clearly. diagnosis is one of the most important aspects of a plant pathologist's training. Without proper

Prevent Plant Disease follow below steps:

1. Follow Good Sanitation Practices.
2. Fertilize to Keep Your Plants Healthy.
3. Inspect Plants for Diseases Before You Bring Them Home.
4. Allow the Soil to Warm Before Planting.
5. Ensure a Healthy Vegetable Garden By Rotating Crops.
6. Provide Good Air Circulation

Fig.5.Detection Page

The AI Engine page allows users to upload images or capture them in real time, while the layered CNN architecture with normalization techniques ensures effective feature extraction and accurate disease prediction. Image preprocessing steps further enhance consistency by standardizing inputs from various sources.

Real-time predictions are enabled through deployment using the Flask framework, allowing users to instantly receive results after submitting a leaf image for analysis.

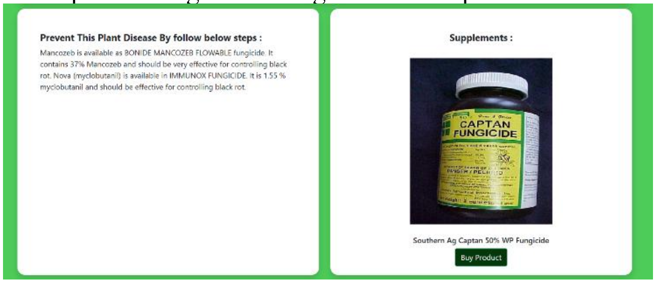
Grape : Black Rot

Brief Descritpion :

Grape black rot is a fungal disease caused by an ascomycetous fungus, Guignardia bidwellii, that attacks grape vines during hot and humid weather. "Grape black rot originated in eastern North America, but now occurs in portions of Europe, South America, and Asia. It can cause complete crop loss in warm, humid climates, but is virtually unknown in regions with arid summers." The name comes from the black fringe that borders growing brown patches on the leaves. The disease also attacks other parts of the plant, "all green parts of the vine: the shoots, leaf and fruit stems, tendrils, and fruit. The most damaging effect is to the fruit"

Fig.6.Grape Black Rot

The system displays the detected disease along with a clear visual representation, helping users understand the condition of the plant through both images and descriptive information.



Prevent This Plant Disease By follow below steps :

Mancozeb is available as BONIDE MANCOZEB FLOWABLE fungicide. It contains 37% Mancozeb and should be very effective for controlling black rot. Nova (myclobutanil) is available in IMMUNOX FUNGICIDE. It is 1.55 % myclobutanil and should be effective for controlling black rot.

Supplements :

Southern Ag Captan 50% WP Fungicide

Buy Product

Fig.7. Prevention and Supplements

Along with the diagnosis, the platform provides preventive steps and suggests suitable supplements or fungicides, giving users actionable guidance to manage the disease effectively.

Corn : Northern Leaf Blight

Brief Descritpion :

Northern corn leaf blight (NCLB) is caused by the fungus Setosphaeria turcica. Symptoms usually appear first on the lower leaves. Leaf lesions are long (1 to 6 inches) and elliptical, gray-green at first but then turn pale gray or tan. Under moist conditions, dark gray spores are produced, usually on the lower leaf surface, which give lesions a "dirty" gray appearance. Entire leaves on severely blighted plants can die, so individual lesions are not visible. Lesions may occur on the outer husk of ears, but the kernels are not infected. On hybrids that contain an Ht gene for resistance to the fungus, lesions are smaller, chlorotic, and may develop into linear streaks. These lesions rarely produce spores.

Fig.8.Corn Northern Leaf Blight

The system also supports multiple crop disease outputs, ensuring flexibility in identifying different plant conditions and offering relevant recommendations accordingly.

Overall, the integration of deep learning with an interactive web application proves to be a fast, practical, and efficient solution for modern agricultural disease detection and management.

VIII.CONCLUSION

This project demonstrates an effective application of Artificial Intelligence in the field of agriculture by enabling accurate plant disease detection using a Deep Learning Convolutional Neural Network (CNN) integrated with a Flask-based web interface. The system is capable of classifying 39 distinct plant disease categories and provides detailed guidance for each, including symptom identification, causes of spread, and suitable prevention or treatment measures. By combining advanced machine learning techniques with an accessible user platform, the solution helps farmers and users make timely and informed decisions regarding crop health. It serves as a practical and scalable approach for improving disease diagnosis and reducing potential crop losses. Moreover, the project highlights the growing importance of AI-driven tools in modern agriculture, promoting efficiency, sustainability, and better management of plant diseases.

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