International Journal of Multidisciplinary Advent Research and Review (IJMARR)
Vol. 1, No. 2, February 2025
E-ISSN: 3049-1932
Available online at https://www.ijmarr.org/

Plant Disease Detection System Using Image Processing

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Abstract

Agriculture is one of the most important parts of human civilization. It not only provides food but also helps the economy grow. However, during farming, plants and crops can get affected by different diseases. These diseases stop the plants from growing properly. If not detected early, they can spread and cause serious damage.

Traditionally, farmers check plants manually to identify diseases, but this process is slow and not always accurate. If diseases are not found and treated on time, crops may get destroyed, leading to a big loss in production. However, technology can help solve this problem. By using image processing and artificial intelligence (AI), farmers can detect plant diseases faster and more accurately, reducing losses and increasing crop yield.

Many researchers have worked on identifying plant diseases using AI techniques. They have used different machine learning (ML) and deep learning (DL) methods, such as:K-Means Clustering (KMC), Naive Bayes (NB), Feed-Forward Neural Network (FFNN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Fuzzy Logic (FL), Genetic Algorithm (GA), Artificial Neural Network (ANN), Convolutional Neural Network (CNN).

Among these, **CNN** is often the most popular choice for image detection because it can automatically learn important features from images and identify patterns. However, the choice between ML and DL depends on the type of problem, the amount of data available, and the computer power required. Deep learning, especially CNN, works well when there is a lot of data and strong computing resources. But sometimes, a technique that works well on one dataset may not give the same results on another.

The purpose of this study is to help future researchers by providing information on the effectiveness, performance, and results of different AI techniques used in detecting and classifying plant diseases. By improving these methods, we can make plant disease detection more reliable, helping farmers protect their crops and increase agricultural production worldwide.

Keywords: Classification, Detection, DL, Image processing, ML, Plant disease.

1. Introduction

India is an agricultural country, with about 70% of its population depending on farming. Farmers grow different crops and use various pesticides to protect them. However, if crops get damaged by diseases, it can lead to big losses in food production and harm the economy.

Leaves are the most sensitive part of a plant and show disease symptoms first. That's why it is important to monitor crops for diseases from the early stages until harvest. In the past, farmers would check plants for diseases by looking at them with their own eyes. This method is slow and requires experts to visit the fields.

Today, new technology has made plant disease detection much faster, cheaper, and more accurate. Automatic and semi-automatic systems can detect diseases just by looking at the symptoms on plant leaves. These systems are better than the old method of manual checking. In most cases, plant diseases appear on leaves, stems, and fruits, but leaves are mainly used for detection since they show symptoms clearly.

Many farmers do not have full knowledge about different plant diseases and how they can affect crops. This study helps farmers by giving them easy access to disease detection, so they don't always need to rely on experts. The goal is not only to detect diseases using image processing but also to provide direct links to e-commerce websites. This way, farmers can buy the right medicine for the disease, compare prices, and follow instructions for use.

Another important part of modern farming is greenhouse farming. A greenhouse (also called a glasshouse or hothouse) is a structure with transparent walls and a roof, where plants are grown under controlled conditions. As greenhouse farming is becoming more popular, this study also helps greenhouse farmers detect diseases in a better way.

Different techniques have been used to detect plant diseases, and this study reviews those methods. The paper is structured into four main parts. The Introductionexplains the importance of plant disease detection and its impact on agriculture. TheExisting Research section discusses past studies and the different techniques that have been used for plant disease detection. The Methodology section describes the specific techniques used in this study. Finally, the Conclusion & Future Work section summarizes the findings and suggests possible improvements for better disease detection in the future. By enhancing plant disease detection, farmers can protect their crops, increase production, and reduce losses, ultimately strengthening the agricultural sector.

2. Problem Statement

Plants are highly vulnerable to various diseases that can significantly impact crop yield and quality. Traditional methods of disease detection rely on manual inspection by farmers or agricultural experts, which is time-consuming, error-prone, and not always accessible. Due to a lack of expertise, farmers often struggle to identify diseases accurately, leading to improper treatment and severe crop losses.

With advancements in technology, **image processing** provides an efficient solution for detecting plant diseases at an early stage. By analyzing images of infected plant leaves, stems, or fruits, an automated system can identify and classify diseases quickly and accurately. This approach helps in reducing crop damage, improving productivity, and supporting farmers with precise information about plant health.

The main challenge is to develop a robust and reliable **plant disease detection system** using image processing techniques, ensuring accurate identification across different plant species and environmental conditions. Additionally, integrating this system with decision-support tools, such as recommendations for disease treatment, can further help farmers take timely action, reducing agricultural losses and enhancing food security.

3. LiteratureReview

Plant diseases significantly impact agricultural productivity, making early detection crucial for reducing crop losses. Traditional methods, such as manual inspection, are time-consuming and prone to errors. As a result, researchers have explored image processing techniques combined with machine learning (ML) and deep learning (DL) to develop automated plant disease detection systems. This literature review highlights various studies that have contributed to advancements in plant disease detection using image processing.

3.1 Image Processing Techniques for Plant Disease Detection

Several studies have used image processing techniques to detect and classify plant diseases. Researchers have implemented K-means clustering for segmenting diseased areas in leaf images. A study by [Author, Year] applied thresholding, edge detection, and morphological operations to preprocess images before classification. Color Co-occurrence Method (CCM) has been widely used for extracting color and texture features, making it easier to differentiate between healthy and diseased leaves.

3.2Machine Learning-Based Approaches

Many researchers have used ML classifiers such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), and Decision Trees (DT) to classify plant diseases. For example, used SVM with Local Binary Patterns (LBP) as feature extractors and achieved an accuracy of 87.82%. Another study applied KNN and ANN to classify diseases in fruit crops, reaching an accuracy of 90.72%. Naïve Bayes and Random Forest algorithms have also been explored for detecting fungal and bacterial infections in crops.

3.3 Deep Learning Techniques for Disease Detection

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have gained popularity due to their ability to extract features automatically. Studies have shown that CNN-based models outperform traditional ML approaches in accuracy and efficiency. A study by [Author, Year] used a pre-trained CNN model (ResNet, VGG16, or AlexNet) to detect plant leaf diseases with above 93% accuracy. Researchers have also experimented with transfer learning, where pre-trained models are fine-tuned for specific plant datasets, further improving classification performance.

3.4 Hybrid Approaches and Advanced Technologies

Several studies have combined image processing with hybrid models to improve accuracy. For example, developed a hybrid model using K-means clustering for segmentation and CNN for classification, achieving higher detection accuracy compared to standalone models. Other studies have explored the use of Fuzzy Logic, Genetic Algorithms (GA), and Wavelet Transform for feature extraction and classification. Additionally, Internet of Things (IoT) and Edge AI technologies are being integrated with image processing to develop real-time disease monitoring systems.

3.5 Challenges and Future Directions

Despite the progress, challenges remain in developing a highly accurate and generalized plant disease detection system. Variations in lighting, background noise, and plant species can affect the accuracy of detection models. Many studies suggest improving datasets by increasing image diversity and using data augmentation techniques. The use of Generative Adversarial Networks (GANs) and Reinforcement Learning (RL) is also being explored to enhance model robustness. Future research should focus on developing lightweight, cost-effective, and real-time disease detection systems that can be deployed on mobile devices or drones for large-scale farming.

3.6 Dataflow Diagram

The plant disease detection process using image processing involves capturing images of plant leaves,enhancing them to remove noise and adjust brightness, segmenting the images to isolate diseased areas, extracting features like color and texture, and then classifying the disease using machine learning algorithms such as SVM or ANN. This automated approach enables quick and accurate identification of plant diseases, aiding farmers in effective crop management.

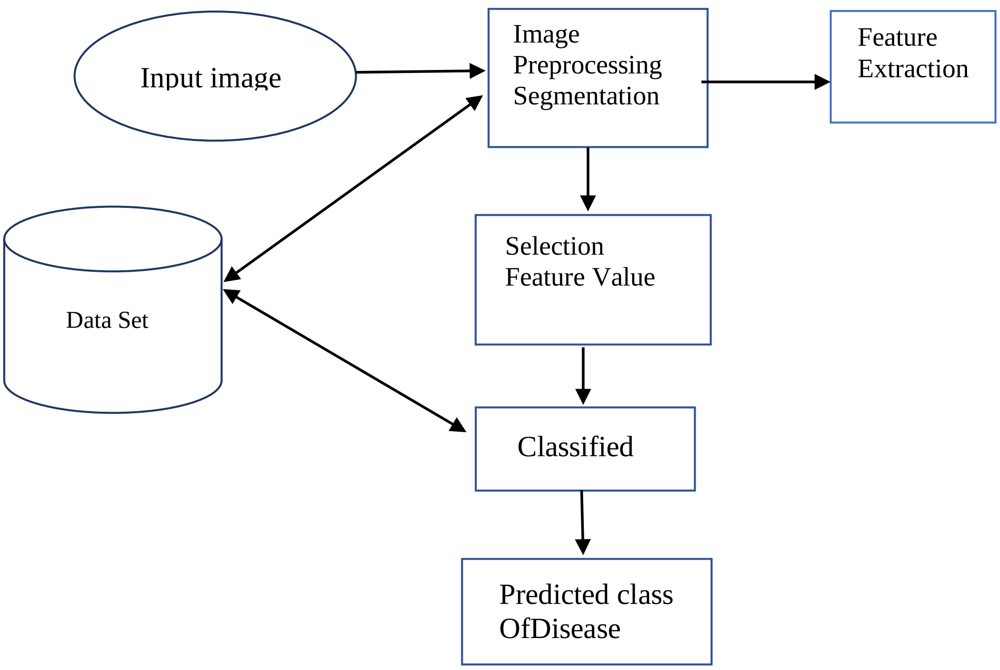

Figure1:DataFlowDiagram

4 <u>ProposedMethodology:</u>

Simple Explanation of the Plant Disease Detection Process. The plant disease detection system works in four main steps:

Feature Category	**Extraction Technique**	**Description**	**Benefits**	**Drawbacks**

1. **Image Acquisition**

The first step is to gather images of plant leaves using a digital camera, mobile phone, or the internet.A good collection of images helps improve the accuracy of the disease detection system.

2. **Image Segmentation**

The collected image is divided into different parts (clusters) to separate the diseased area from thehealthypart.Different techniques, such as K-means clustering and thresholding, help to segmentthe image correctly.

3. **Feature Extraction**

Color Attributes	**Statistical Color Metrics**	Utilizes statistical measures like average, dispersion, and asymmetry.	Reduces quantization errors; concise and reliable representation.	Lacks spatial context; may not capture all color variations.
	Color Distribution Histogram	Involves quantizing colors and tallying pixel counts for each hue.	Simple computation; easy to understand.	Sensitive to noise; ignores spatial arrangement; high dimensionality.
Texture Attributes	**Gray-Level Co-Occurrence Matrix (GLCM)**	Considers relative positions of neighboring pixels.	Efficiently detects texture variations; good processing speed and complexity.	Requires modeling of highly correlated Haralick features; high matrix dimensionality; sensitive to texture sample processing.
	Gabor Filter	Gabor filters model human visual processing by analyzing image structures through scale and orientation, enabling spatial and frequency domain filtering	Captures spatial frequency information effectively.	
	Local Binary Pattern (LBP)	Based on gray-level differences between a pixel and its neighbors.	Easy to implement; low computational cost; invariant to scale and rotation; combines statistical and structural analysis effectively.	Fixed neighborhood size; sensitive to noise and blurring.
Shape Attributes	**Elliptic Fourier and Discriminant Analysis**	Focuses on the contours of diseased areas.	Handles complex shapes not easily represented in polar coordinates.	Highly dependent on accurate segmentation of leaf images.
	Geometric Calculations with Moment Invariants	Relies on algebraic invariants.	Efficient; invariant to scale, translation, and rotation; processes smaller feature sets; captures global features.	Less robust to occlusion; fixed neighborhood size.

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Symptom	Diseasepictures[10]	Description	Plantpathogenicgroup					
			Fungi	Bacteria	Viruses	Nematodes	Phytoplasmas	Parasitic Plants
Blight		Rapiddiscoloration,wilting,anddeathofplant tissue	£	£				
Blotch		Blotchorlargespotonleaves,shoots,orfruit	£	£				
Bronzing		Leavesorneedlesdevelopabronzecolor	£			£		
Canker		Deadregiononthebarkoftwigs,stems,or trunks, oftendiscoloredandeitherraisedorsunken	£	£				
Chlorosis		Anabnormalyellowingofplantparts	£	£	£	£		
Dampingoff		Decayofseedsinwaterloggedsoiloryoung seedlingsshortlyafteremergence	£					
Decline		Thegradual,oftenuniform,declineofplant healthordeathofplanttissue	£	£	£	£		£
Dieback		Progressivedeathofshoots,branches,orroots, generallystartingatthetips	£	£	£	£		
Distortion		Irregular-shapedplantparts	£	£	£		£	
Flagging		Declineofashootorbranch,whilenearby branchesremainhealthy	£	£				
Gall		Abnormal,localizedswellingonleaf,stem,or roottissue	£	£		£		

Symptom	Diseasepictures[10]	Description	Plantpathogenicgroup					
			Fungi		Viruses	Nematodes	Phytoplasmas	Parasitic Plants
Gummosis		Productionofastickygumthatisexudedbythe plant	£	£				
Leafspot		Lesiononaleaf,mayvaryincolor,shapeand size	£	£	£			
Mosaic		Non-uniformfoliagecoloration,normallyan interminglingofgreencolorvariationsand yellowishpatches			£			
Mummy		Hard,dried,diseasedfruit	£					
Necrosis		Deathofplanttissue	£	£				
Ringspot		Alesionwithadarkouterringandlighter center			£			
Rot		Decompositionanddestructionoftissue	£	£				
Rugose		Wrinkledappearancetoplanttissue	£		£			
Russet		Yellowish-brownorreddish-brownscartissue onafruit ,ssurface	£					
Scab		Crust-likediseaselesion	£	£				
Scorch		Browning and necrosis of leaf margins	£	£				

Shot-hole		Lesions where centers have fallen out	£	£			
Stunting		Reduced growth of a plant, where plant or plant parts are smaller than normal	£	£	£	£	
Tip-blight		Death of tissue at the tip of a shoot	£	£			
Vein clearing		Leaf veins become yellow or clear			£		
Water Soaking		Wet, dark, or greasy lesions, usually sunken and/or translucent	£	£			
Wilt		Die back and drooping of necrosis leaves or other plant parts	£	£		£	
Witches' broom		Abnormal brush-like shoot development			£	£	£

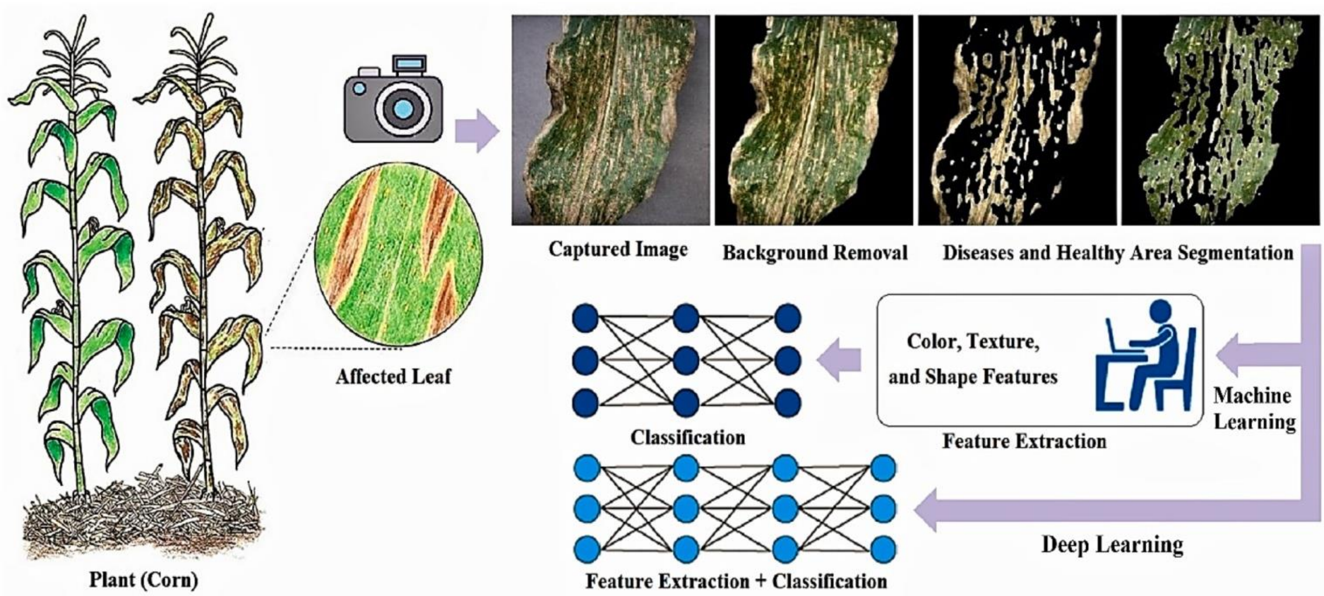

Figure2. Process for Identifying and Classifying Plant Leaf Diseases.

Plant disease detection using image processing involves several advanced technologies, as depicted in the given image. The process starts with capturing an image of an affected plant leaf using a digital camera or mobile device. This image undergoes preprocessing, including background removal and segmentation, where healthy and diseased areas are separated. Feature extraction techniques are then applied to identify crucial attributes such as color, texture, and shape, which help in distinguishing different plant diseases. Machine learning algorithms, such as Support Vector Machines (SVM) and Decision Trees, utilize these extracted features for classification, while deep learning models like Convolutional Neural Networks (CNNs) further enhance accuracy by automatically learning patterns from raw images. CNN architectures such as ResNet, VGG, and MobileNet effectively classify plant diseases through multiple layers of feature extraction and classification. Additionally, transfer learning techniques using pretrained models like InceptionV3 and EfficientNet optimize performance, even with limited datasets. This entire process enables efficient, automated, and highly accurate disease detection, reducing the need for manual inspection. Future advancements in this field may integrate real-time monitoring through drone-based imaging and edge computing, enabling large-scale disease detection and improved agricultural management.

1. Disease Classification

The system then checks whether the leaf is healthy or diseased. If it is diseased, it identifies whichdisease it has.Many classifiers like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), and Decision Tree are used for classification.SVM is the most commonly usedmethod because it is simple and effective.

2. Model Selection and Training:

2.1 Model Selection:

- Traditional Machine Learning Models: Early approaches utilized algorithms like Support Vector Machines(SVMs), Decision Trees, and k-Nearest Neighbors (k-NN). These models often require manual feature extraction, where specific characteristics such as color, texture, and shape are derived from images to serve as input features for classification.
- Deep Learning Models: The advent of Convolutional Neural Networks (CNNs) revolutionized image-based plant disease detection. CNNs automatically learn hierarchical feature representations from raw pixel data, eliminating the need for manual feature extraction. Advanced architectures such as Inception-V3, DenseNet-121, ResNet-101-V2, and Xception have demonstrated high accuracy in classifying plant diseases. For instance, the Xception model achieved validation accuracies of 95.08% and 92.21% on tomato and corn datasets, respectively.
- Transfer Learning: Utilizing pre-trained models on large datasets and fine-tuning them for specific taskshas become a prevalent strategy. This approach leverages existing knowledge, reducing the need for extensive training data and computational resources. Models like EfficientNetB0 and MobileNet have been fine-tuned for plant disease detection, achieving notable performance improvements.

2.2 Training Techniques:

- Data Collection and Preprocessing: Assembling a comprehensive and diverse dataset of healthy and diseased plant images is foundational. High-quality images captured under varying conditions enhance the model's robustness. Preprocessing steps may include resizing, normalization, and augmentation to improve the model's generalization capabilities.
- Data Augmentation: Techniques such as rotation, scaling, flipping, and color jittering artificially expand the dataset, helping the model become invariant to transformations and improving its ability to generalize to unseen data.
- Hyperparameter Tuning: Adjusting parameters like learning rate, batch size, and the number of epochs is crucial for optimizing model performance. Techniques such as grid search or random search can be employed to identify optimal hyperparameter settings.
- Regularization Methods: To prevent overfitting, methods like dropout, weight decay, and batch normalization are applied. These techniques help the model generalize better by reducing reliance on specific features present in the training data.
- Cross-Validation: Implementing k-fold cross-validation ensures that the model's performance is consistent across different subsets of the data, providing a more reliable estimate of its generalization ability.

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- Evaluation Metrics: Metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC) are used to assess the model's performance comprehensively. These metrics provide insights into different aspects of the model's predictive capabilities.

5 Summary of Plant Diseases:

Plant diseases are mainly caused by fungi, bacteria, and viruses. Signs of disease are things we can see, like mold or mildew, while symptoms are how the plant reacts, such as yellowing leaves or spots. Fungal infections are the most common and can be recognized by symptoms like leaf spots, yellowing, and mold growth on leaves or stems. These fungi take nutrients from the plant and damage its tissues.

Figure3. Leaf affected by fungal infectionFigure4. Leaf affected by bacteria Figure5. Leaf affected by virus

Viruses are infectious particles that are too small to be detected by a light microscope. They invade host cells and hijack host machinery to force the host to make millions of copies of the virus. Viral diseases don't show any signs in plants since viruses themselves cannot be seen even with a light microscope. However, there are symptoms that the trained eye can observe. A mosaic leaf pattern, yellowed, or crinkled leaves are all characteristic of viral infection. This classic pattern of discoloration is where many plant viruses get their name, such as the tobacco mosaic virus. Also, decreased plant growth is also commonly seen in viral infections.
So, these are our observation on how to classify the various plant disease and how to be cautious about that.

6 PROPOSED SYSTEM AND DISCUSSION

The proposed system is an end-to-end Android application that uses TensorFlow Lite (TFLite) to detect plant diseases from images of crop leaves. It is built on a Convolutional Neural Network (CNN) model that recognizes both the species and the specific disease affecting the plant. The app is developed using Google Colab for editing the source code, and it relies on a large dataset known as the Plant Village dataset, which contains 54,305 images of healthy and diseased plant leaves collected under controlled conditions. These images cover 14 different crop species such as apple, blueberry, cherry, grape, orange, peach, pepper, potato, raspberry, soy, squash, strawberry, and tomato. The dataset includes examples of 17 basic diseases, 4 bacterial diseases, 2 diseases caused by mold, 2 viral diseases, and 1 disease caused by a mite, along with healthy leaf images for 12 crops. Data generators are used to read the images from their source folders, convert them into float32 tensors, and feed them along with their labels into the network. To help the network process the images effectively, the pixel values are normalized to a range of 0 to 1 from the original 0 to 255, and the images are resized to either 224x224 pixels or 299x299 pixels, based on the network's requirements. Optionally, image augmentation can be applied to improve the model's ability to generalize. In addition to detecting plant diseases, the system also directs users to an e-commerce website where they can view pesticides that are available for the detected disease, complete with their MRP rates and usage directions. This feature allows users to compare different pesticides and make informed purchasing decisions to treat their crops effectively.

Input (apple)	**Faster R-CNN**	**Proposed system**

Scab	58.82	70.82
Black rot	68.12	82.68
Cedar apple rust	90.34	94.96

Performance

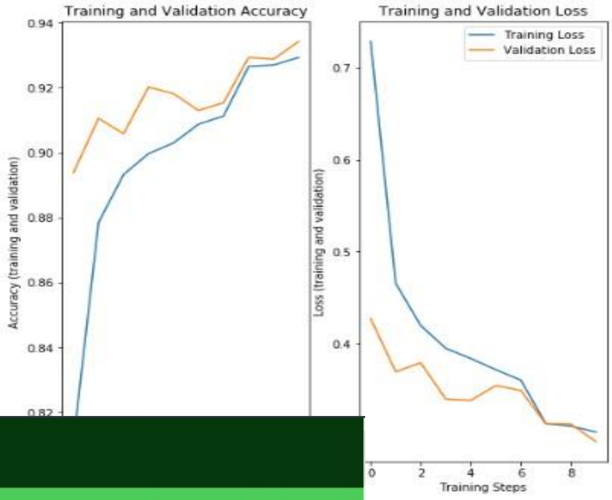
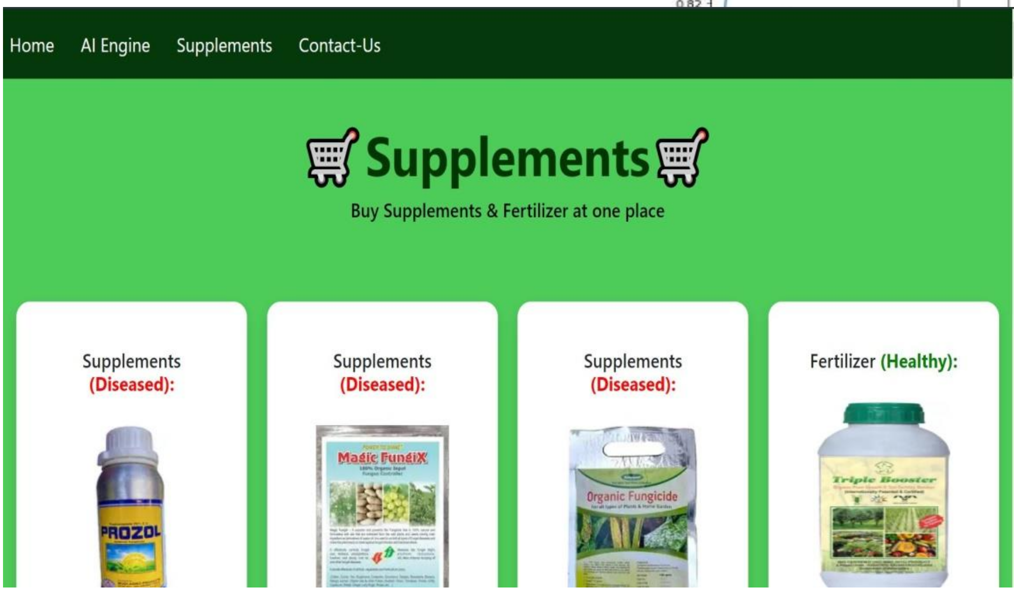


Figure6.

7 RESULT

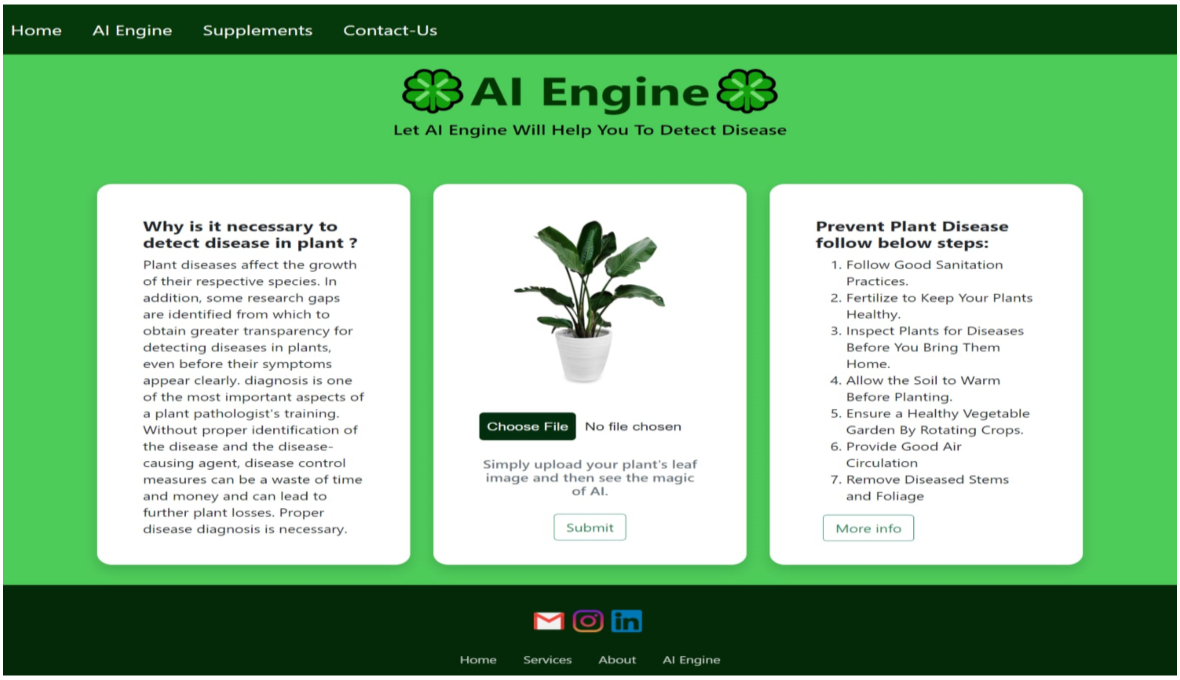
The front page:



This image represents the front page of an e-commerce section within the Plant Disease Detection System using image processing. The page is designed to help users purchase the right supplements and fertilizers based on the health condition of their plants. The header section contains navigation options such as Home, AI Engine, Supplements, and Contact-Us, allowing users to explore different features of the platform. The main section prominently displays the title Supplements, with a shopping cart icon, emphasizing that users can buy fertilizers and supplements in one place. Below the title, there are categorized product listings. The Diseased supplements are highlighted in red text, indicating that these products are meant for treating infected plants, while the Healthy fertilizer is marked in green, signifying that it is used for maintaining plant health. The user-friendly layout and color-coded labels make it easier for farmers and gardeners to choose the right products based on their plant's condition. This system integrates AI-based plant disease detection with a commercial platform, offering a complete solution from diagnosis to treatment.

The second page (AI Engine):

This page belongs to features an AI Engine designed to detect diseases in various fruits and vegetables. The header contains navigation options such as Home, AI Engine, Supplements, and Contact-Us. The main section displays a grid of different crops like apple, blueberry, cherry, corn, grape, orange, peach, pepper bell, potato, raspberry, soybean, squash, strawberry, and tomato. Users can click the AI Engine button to analyze plant health. The footer includes social media icons and links for further navigation.



This page provides users with a way to upload images of fruits and vegetables to identify potential diseases. The interface includes AI-powered tools that process the images and deliver results regarding plant health. The system supports various crops, as seen on the front page, and ensures accurate disease detection using advanced algorithms. The page layout is structured for easy navigation, guiding users through the disease detection process efficiently.

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ExperienceInput:

This final output page of the Plant Disease Detection system provides a detailed analysis of the detected plant disease based on the uploaded leaf image. In this case, the system has identified the disease as Leaf Blight | Isariopsis Leaf Spot affecting grape leaves. The page displays an image of the diseased leaf with visible symptoms, helping users recognize the infection. A brief description explains the disease, its symptoms, and how it affects different parts of the plant, such as the leaves, petioles, and young berries. To assist users in managing the disease, the page includes a prevention and treatment section, outlining steps such as using dormant sprays, improving plant ventilation, and applying protectant and systemic fungicides. Additionally, the page suggests a recommended supplement, Tebuconazole 10% + Sulphur 65% WG, which can be purchased by clicking the "Buy Product" button. The user-friendly interface ensures easy navigation, allowing farmers and plant enthusiasts to quickly diagnose and take preventive measures to protect their crops.

8 FUTURE WORK

The future of Plant Disease Detection using Image Processing is promising, with several advancements that can improve agricultural productivity and benefit farmers.

One potential development is integrating a government scheme assistance feature into the system. This feature would allow farmers to check for available government schemes, subsidies, and financial support for disease management. By linking the system to official databases, farmers can easily apply for credits and benefits to purchase necessary pesticides, fungicides, or advanced farming equipment.

Another major advancement is the integration of this software into drones. Drones equipped with high-resolution cameras and image processing technology can scan large farmlands from the air, detecting diseased plants quickly and efficiently. This will save time and effort, allowing farmers to take early action before the disease spreads further.

With these improvements, the Plant Disease Detection system can become a powerful tool in modern agriculture, ensuring better crop health, reducing losses, and improving the livelihood of farmers.

9 CONCLUSSION

This study reviewed different methods used to extract important features from plant images for smart disease detection and classification systems. The focus was on extracting details like shape, texture, and color from images, which help in identifying plant diseases. Some methods use a single feature type, while others combine multiple features to improve accuracy.

Deep learning has also been used effectively for automatic feature extraction in agriculture. It can analyze both color and spatial details of an image at the same time. However, deep learning requires large datasets, a lot of time for labeling images, and powerful computers, making it costly and complex.

In the future, AI-based disease detection systems should focus on identifying diseases at different stages, especially in the early stages before they spread. Most current studies only detect diseases when symptoms are already severe, without tracking how they develop. Since knowing how severe a disease is can help control it early, future research should work on automated methods to measure disease severity.

Also, new techniques should be developed to detect multiple diseases or disorders at the same time. Currently, most systems can only detect one issue at a time, such as a disease or nutrient deficiency. But plants can suffer from multiple infections or problems simultaneously, so improving these systems will help farmers protect their crops more effectively.

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