Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2s (2026) | 422-429

Plant Leaf Disease Detection System

Pranav Kadam[1], Nikhil Mhetre[2], Sameet Parate[3], Shankhanath Suryavanshi[4], Mayuri Fegade[5]

[1,2,3,4,5]Department of AI & DS, Dr. D. Y. Patil College of Engineering & Innovation, Varale, Pune, India.
[1]pranavkadam742@gmail.com, [2]mhetrenikhil655@gmail.com, [3]sameetparate18@gmail.com, [4]suryvanshishankanath@gmail.com, [5]mayuri.fegade@dypatilef.com

Peer Review Information

Type: *Article*
Received: *23 April 2026*
Revised: *09 May 2026*
Accepted: *22 June 2026*
Published: *18 July 2026*

Abstract

Plant diseases pose a significant threat to agricultural productivity and food security. Early and accurate detection of leaf diseases is essential to minimize crop loss and improve yield quality. This project focuses on detecting plant leaf diseases using deep learning techniques. A CNN model is used to analyze leaf images and identify diseases accurately. The system improves detection speed and helps farmers take timely actions to protect crops.The proposed system processes leaf images through preprocessing steps such as resizing, normalization, and augmentation, followed by feature extraction and classification using a trained cnn model. The model is trained on a publicly available dataset and achieves an accuracy of approximately 92%. The system provides fast and reliable disease identification, making it suitable for real-time agricultural applications. This approach reduces dependency on manual inspection and helps farmers take timely corrective actions.

Keywords: Deep Learning; Diagnosis; Image Processing; Machine Learning; Plant Disease.

How to Cite This Article

Kadam, P., Mhetre, N., Parate, S., Suryavanshi, S., & Fegade, M. (2026). Plant leaf disease detection system. *Multidisciplinary Journal of Research in Engineering and Technology, 13*(2s), 422–429.

Introduction

Agriculture is one of the most important sectors in India, supporting millions of people. However, plant diseases reduce crop quality and yield, causing major losses to farmers. However, plant diseases significantly affect crop productivity and quality, leading to economic losses and food insecurity. Early detection and proper diagnosis of plant diseases are essential to ensure healthy crop production and sustainable agriculture.Traditionally, plant disease detection is performed through manual observation by farmers or experts. This approach is time-consuming, requires domain expertise, and is often prone to human error. In many rural areas, access to agricultural experts is limited, making timely diagnosis difficult. With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated systems have been developed to detect plant diseases using image processing techniques. Among these, Deep Learning models, particularly Convolutional Neural Networks (CNN), have shown remarkable performance in image classification tasks due to their ability to automatically extract relevant features. In this research, a Plant Leaf Disease Detection

System is proposed using a CNN-based approach. The system analyzes images of plant leaves, identifies patterns associated with diseases, and classifies them accurately. This method not only improves detection accuracy but also reduces the time and effort required for diagnosis. The proposed system aims to assist farmers by providing a fast, reliable, and cost-effective solution for disease detection. It can be further integrated into mobile or web applications, enabling real-time usage in agricultural fields.

Plant Disease/Types and Symptoms

Our system uses deep learning to identify plant diseases from leaf images. It accepts an image as input, processes it, and determines whether the leaf is healthy or infected. Plant diseases are generally classified into two types: biotic and abiotic. Biotic diseases are caused by living organisms such as bacteria, fungi, and viruses, while abiotic diseases result from environmental factors like temperature, moisture, or nutrient imbalance. In this study, we mainly focus on biotic diseases.

Bacterial Disease Bacterial infections in plants usually appear as small water-soaked spots on leaves. Over time, these spots grow larger and turn into dry, dead patches. In some cases, leaves may show dark or brown spots surrounded by yellow areas. Under dry conditions, these spots may appear scattered across the leaf surface. A common example is bacterial wilt in crops like brinjal, where the entire plant may collapse due to infection.

Viral Disease- Viral diseases are difficult to identify because their symptoms are often unclear and may resemble nutrient deficiencies or chemical damage. Infected plants may show patterns such as yellow or green stripes on the leaves. These viruses are commonly spread by insects like aphids, whiteflies, and leafhoppers. One typical example is mosaic disease, which affects the color and texture of leaves as shown in Fig. 2 (b).

Fungal Disease- Plants fungal disease affects various components of plants i.e., sclerotium wilt, common crown rot, stem rust, eyespot (sheath or stem), rust, blight (leaves), ergot (spikes) and carnal bunt, black point (seeds). These diseases often appear as spots, patches, or mold-like growth on plant surfaces. For example, late blight caused by *Phytophthora* results in grayish-green, water-soaked spots that later darken and develop fungal growth. Early blight, caused by *Alternaria*, produces brown spots with circular ring patterns. Rust disease forms small colored spots on leaves, which may later turn dark. These infections are often influenced by environmental conditions such as humidity and temperature as shown in Figure 2(e). This blemish becomes black after green-yellow.

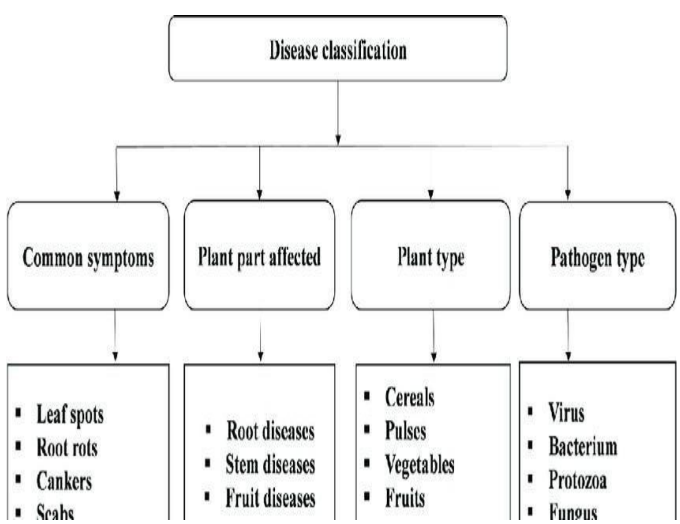

Fig. 1. *Classification of plant disease in distinct categories*

(a) health (b) micro-stage (c) early (d) middle (e) later (f) advanced

Fig. 2. *Disease Leaf*

Table 1. *Classification of plant disease in distinct categories*

Crop Types	Crop Names	Disease Names	Disease Types	Main Infected Sites	Sensors/Platforms/Scales	Analysis Approach	References
Cereal Crops	Wheat	Wheat stripe rust	Fungal diseases	Leaves *	Analytical spectral device (ASD)/handheld/leaves and canopy	Partial least squares discriminant analysis (PLSR), support vector regression (SVR), and Gaussian process regression (GPR)	[49]
		Wheat leaf rust	Fungal diseases	Leaves *	ASD and digital camera/handheld/leaves	Linear spectral mixture analysis, Fisher function	[50]
		Wheat powdery mildew	Fungal diseases	Leaves *	ASD/handheld/canopy	Continuous wavelet analysis, Fisher's linear discrimination analysis (FLDA) and support vector machine (SVM)	[51]
		Fusarium head blight	Fungal diseases	Ears * and stalks	ImSpector V10E and ImSpector N25E/indoor measurement platform/spikelets	Linear model fitting, spectral vegetation indices (SVIs)	[42]
	Rice	Rice sheath blight	Fungal diseases	Leaves *	ImSpector V10E/indoor measurement platform/single plant	Linear discriminant analysis (LDA) and SVM	[52]
		Rice blast	Fungal diseases	Leaves *, stems and ears	ORCA-05G/darkroom/panicle	"Bag of spectra words" (BoSW) model and chi-square support vector machine (chi-SVM)	[53]
	Maize	Grey leaf spot disease	Fungal diseases	Leaves *	ASD and three multi-spectral satellite Resampled/handheld/satellite/leaves and canopy	Random forest algorithm (RF)	[54]
		Leaf spot disease	Fungal diseases	Leaves * and bracks	ASD/handheld/leaves	Guided regularized random forest (GRRF) and RF	[55]
		Ear rot	Fungal diseases	Ears and kernels *	SisuChema/HgCdTe detector/fungal isolates	Principal component analysis (PCA) and PLSR	[56]
Legume Crops	Soybean	Soybean anthracnose	Fungal diseases	Stems *, pods and leaves *	Pika XC/mounting tower/stems	Genetic algorithm as an optimizer and SVM as a classifier	[57]
		Yellow mosaic virus	Viral disease	Leaves *	ASD/handheld/leaves	Spectral derivative and red edge analysis	[58]

Plant Disease Detection System

Our system detects plant diseases from leaf images using a CNN-based deep learning approach. It accepts a leaf image as input, which can be captured using a smartphone or taken from an existing dataset. Before processing, the image is resized and normalized to improve its quality, and noise is reduced to make the features clearer. The processed image is then passed to a Convolutional Neural Network (CNN), which automatically learns important patterns such as color, texture, and shape. Based on these features, the model classifies the leaf as either healthy or affected by a specific disease. The final layer uses a Softmax function to calculate the probability of each class, and the system displays the predicted disease along with a confidence score. We trained the model using a labeled dataset such as PlantVillage to achieve better accuracy and reliability. This approach reduces manual effort and enables faster detection of plant diseases. The system is implemented using Python and deep learning libraries like TensorFlow/Keras, and it can be further developed into a mobile or web application for real-time use in agriculture.

Machine Learning Using Image Processing

In this system, plant disease detection using machine learning follows a series of important steps. First, images of plant leaves are collected either using a camera or from available datasets. These images are then improved through preprocessing techniques such as resizing, noise removal, and normalization to make them suitable for analysis. After that, the image is segmented to separate the affected region of the leaf from the background. The segmented portion is used to extract useful features like color, texture, and shape, which help in identifying disease patterns. Finally, these features are given to a classification model that determines whether the leaf is healthy or infected. This step-by-step process helps in improving the accuracy and efficiency of the disease detection system.

1. Image Acquisition

The initial gait for any machine learning system is image acquisition. This incorporates image capture or redeems images from repositories. The image quality highly leans on 37446 VOLUME 12, 2024 A. Bhargava et al.: Plant Leaf Disease Detection, Classification, and Diagnosis the camera and its acclimatization which leads to disease detection accuracy of the system. The captured image might dwell in the undesired background, adumbration, and noise. To improve the accuracy of the system or to extract the affected part firstly background removal and noise removal are required. Subsequently, other than RGB images from normal cameras, certain specific cameras are used to capture hyperspectral, thermal, and fluorescent images. Various researchers use distinct datasets for plant disease detection systems as indicated in Table 3. The presence of shadow, light, insufficient lighting, and intricated background is burdensome due to uncontrolled/real-time images as compared to laboratory surroundings conditions. The quality of the image captured robustly depends upon the techniques and equipment used. Consequently, the system performance is influenced by the image acquisition stage.

2. Image Pre-Processing

The crucial step in a machine learning system is image processing. It helps to improve the quality of the image that is degraded due to distortions, turbulence, or shadow]. Majorly, the dataset is captured in uncontrolled environments or real-time situations. Therefore, the preprocessing step is necessary before feature extraction enlarges the estimated accuracy of the system which results in reduced processing time. The process also reduces the processing time by applying operations such as crop, and resize. The literature utilizes image enhancement, cropping, and elimination of background as extensively used preprocessing techniques. These operations applicability depends on the image quality. Image preprocessing along with augmentation is used to create more images of the data on the existing data for several deep learning techniques that require large amounts of image data. The processing augmentation techniques are noise injection, flipping of image, gamma correction, scaling, rotation, resize, cropping, random shift, zoom, and image transformation such as contrast enhancement and brightness.

3. Image Segmentation

The region of interest or undesired region can be segregated using image segmentation. This approach intends to separate the part having a deformity. This analysis of the representation of the image is simple and further meaningful to discriminate the affected and unaffected parts. It is the most important technique among machine learning techniques as critical issues and techniques in the analysis of an image. The several challenges faced such as erroneous boundaries of the affected region, shadow, illumination, and complex background. The segmentation process is classified into two main divisions: first is conventional methods such as thresholding, region growing and edge detection other is computational techniques such as fuzzy logic, genetic algorithm(Table2). Details of the dataset available used by various researchers. and neural network. Generally, computational techniques perform better than conventional techniques. The segmentation process is crucial for the extraction of features.

Table 2. *Datasets Used in Plant Disease Detection*

Dataset Name	**No. of Images**	**No. of Classes**	**Type of Data**	**Key Features**	**Used By Researchers For**
PlantVillage	54,000	38	Lab-controlled images	High-quality, labeled dataset	CNN training & classification
PlantDoc	2,500	27	Real-world images	Complex background, natural conditions	Real-time model testing
IP102	75,000	102	Field images	Large-scale dataset with pest & disease classes	Advanced deep learning models
PlantSeg	7,700	115	Annotated images	Pixel-level segmentation annotations	Disease segmentation
CropDisease	10,000+	multiple	Mixed (lab + field)	Diverse crop diseases	Multi-class classification
Rice Leaf Dataset	3,000	4-5	Field images	Focused on rice diseases	Crop-specific research

4. Feature Extraction

To discriminate one part of an image from another part, feature attribute extraction is one of the most important techniques in computer vision/ machine learning systems. Details of segmentation technique used by various researchers. before classification. The features are advantageous to analyze objects and to allow the class label to an object. Generally, in the literature color, shape, and texture features are utilized for recognition. The classification of plant disease detection systems is enormously dependent upon the techniques used for image characteristic extraction. From the literature, the spotted area segmentation and texture, color & shape feature extraction are of huge importance. Several plant disease detection researchers have used distinct convenient feature extraction techniques depending on texture, color & shape. Therefore, determining the correct features is a major issue in the detection of disease due to similarity in disease characteristics. In computer vision/ machine learning applications, the selection of relevant features is also important to prevent overfitting and huge computational costs. Therefore, in computer vision and machine learning applications feature selection approaches are selected to find better relevant features from the extracted features. Some of the techniques such as PCA, genetic algorithm, and particle swarm optimization are used for feature selection. The literature utilizes various feature extraction techniques. By examining these approaches, an attempt is made to find the better-suited technique.

Table 3. *Feature Extraction Techniques and Authors*

Technique	Author(s)
Color Feature Extraction	Patil & Kumar (2011)
Texture Features (GLCM)	Haralick et al. (1973)
Shape Feature Extraction	Du & Sun (2004)
SIFT (Scale-Invariant Feature Transform)	Lowe (2004)
HOG (Histogram of Oriented Gradients)	Dalal & Triggs (2005)
CNN Feature Extraction	LeCun et al. (1998)
Transfer Learning (VGG, ResNet)	Simonyan & Zisserman (2014), He et al. (2016)
Autoencoders	Hinton & Salakhutdinov (2006)

5. Classification

The utmost extrusive stage in computer vision/ machine learning is classification. The attainment of this step builds upon antecedent steps such as acquisition, preprocessing, and feature extraction/ selection. The manuscript is focused on disease detection in plants the above steps are used for detection based on category and symptoms. In this system, a dataset is trained first and then used to classify the test image as healthy/defective. ''Machine learning (ML) is an application of artificial intelligence (AI) which provides you a system an ability to automatically learn, improve from experiences without being explicitly programmed and which can make decisions.'' ML techniques have been broadly distinguished as Supervised ML and Unsupervised ML. During the training process the labeled and unlabeled data work for supervised and unsupervised techniques respectively. The semi-supervised ML is another special supervised learning that works on both labeled and unlabeled data during the training process. In the literature, various classification techniques are utilized. Generally, support vector machine (SVM), artificial neural network (ANN), and k-nearest neighbor (k-NN) have been adapted for machine learning techniques. Also, in a few studies vegetation index and fuzzy logic feature-based techniques are utilized. Distinct models of ANN like feedforward NN, error backpropagation, multilayer perceptron, probabilistic neural network, and self-organizing map have been widely utilized for plant disease detection. the quality investigation of plant disease detection based on distinct classification techniques used by distinct researchers.

Deep Learning Using Image Processing

Deep learning (DL) was first proposed in 1943 as a hierarchy of machine learning for the detection of objects classification of images as well as processing of natural language. DL forms high-level features by combining low-level features for distributed features discovering and sample data attributes. The ability of generalization and accuracy are enhanced compared to traditional ML techniques for target detection and image recognition. The development of DL is in three phases. Phase 1, during 1943-1969 was a linear model of neural network for classification. Phase 2, during 1986-1988 was a non-linear mapping of multi-layer perceptron for the BP (Backpropagation) algorithm. Phase 3, from 2006 to the present, has a ReLu activation function, ImageNet recognition, and deep learning model-AlexNet. The DL methods are

1. Image Acquisition

Image acquisition is the first and most important step in the Plant Disease Detection System. In this stage, images of plant leaves are collected to serve as input for further processing and analysis. The quality and diversity of the acquired images directly affect the performance and accuracy of the system. Leaf images can be captured using digital cameras, smartphones, or obtained from publicly available datasets such as the Plant Village dataset. The images should include both healthy and diseased leaves under different environmental conditions, such as varying lighting, background, and angles, to ensure robustness of the model. To maintain consistency, images are typically captured in high resolution and then resized to a standard dimension (e.g., 224×224 pixels) before processing. Proper image acquisition helps in capturing essential features like color variations, texture patterns, and disease spots, which are crucial for accurate classification. In the proposed system, a large dataset of labeled leaf images is used to train the deep learning model. The diversity in the dataset improves the generalization capability of the model, enabling it to perform well on real-world inputs.

2. Image Augmentation

Image augmentation is a technique used to artificially increase the size and diversity of the training dataset by applying various transformations to the original images. It plays a crucial role in improving the performance and generalization ability of deep learning models, especially when the available dataset is limited. In plant disease detection, leaf images may vary due to changes in lighting conditions, orientation, background, and scale. Image augmentation helps the model become robust to such variations by exposing it to different versions of the same image. Common augmentation techniques include rotation, horizontal and vertical flipping, scaling, zooming, cropping, and brightness adjustment. These transformations do not alter the core features of the image but provide new perspectives for the model to learn. In the proposed system, image augmentation is applied during the training phase using tools such as ImageDataGenerator. This ensures that the Convolutional Neural Network (CNN) learns invariant features and reduces the risk of overfitting. By increasing the diversity of the dataset, image augmentation significantly enhances the accuracy and reliability of the plant disease detection system.

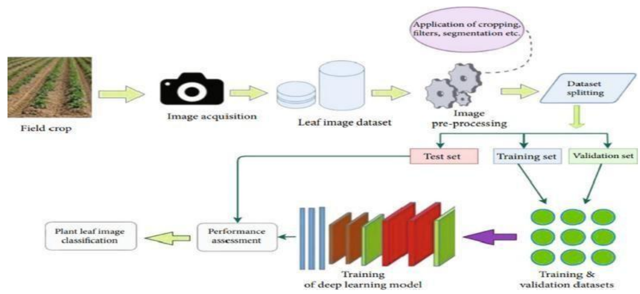

Fig. 3. *Process of ML*

3. Image Classification

Image classification is the final stage of the Plant Disease Detection System, where the processed leaf image is categorized into different classes such as healthy or diseased. This step plays a crucial role in identifying the type of disease affecting the plant. In the proposed system, classification is performed using a Convolutional Neural Network (CNN). After feature extraction through convolutional and pooling layers, the high-level features are passed to fully connected layers for classification. The final output layer uses the Softmax activation function to assign probabilities to each class. The model is trained on a labeled dataset containing various plant leaf images, where each image corresponds to a specific disease category. During training, the model learns patterns and distinguishing features such as color changes, texture variations, and lesion shapes associated with different diseases. Once trained, the model can classify new, unseen images with high accuracy. The output of the system includes the predicted disease label along with a confidence score, which helps in making reliable decisions. Accurate image classification enables early detection of plant diseases, allowing farmers to take timely preventive measures and improve crop productivity.

Hyperspectral Imaging Using Image Processing

Hyperspectral Imaging (HSI) is an advanced image processing technique that captures and analyzes a wide spectrum of light beyond the visible range. Unlike traditional RGB images, which consist of three color channels, hyperspectral images contain hundreds of spectral bands. This allows for detailed analysis of plant leaf properties and enables early detection of diseases that may not be visible to the human eye. In plant disease detection, hyperspectral imaging is used to identify subtle changes in leaf pigmentation, moisture content, and cellular structure. Each disease affects the spectral signature of a plant differently, and HSI can capture these variations effectively. This makes it highly useful for detecting diseases at an early stage, even before visible symptoms appear. The hyperspectral data is first acquired using specialized sensors and then processed using image processing techniques such as noise reduction, normalization, and dimensionality reduction. Since hyperspectral images contain large amounts of data, techniques like Principal Component Analysis (PCA) are often used to reduce complexity while preserving important features. Machine learning and deep learning algorithms are then applied to the processed data for classification. Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) are commonly used for analyzing hyperspectral images. These models learn the spectral patterns associated with different diseases and provide accurate classification results.

Few Shot Learning (FSL) Using Image Processing

Few-Shot Learning (FSL) is an advanced machine learning approach that enables models to learn and generalize from a very limited number of training samples. In the context of plant disease detection, FSL is particularly useful when large labeled datasets are not available, which is often the case for rare or newly emerging plant diseases. Traditional deep learning models require a large amount of labeled data to achieve high accuracy. However, collecting and annotating such datasets can be time-consuming and costly. Few-Shot Learning addresses this limitation by training models to recognize patterns from only a few examples per class. In image processing-based plant disease detection, FSL techniques use methods such as metric learning, Siamese networks, and prototypical networks. These models learn to measure similarity between images rather than directly classifying them. When a new image is provided, the model compares it with a few known examples and determines the closest match based on learned features. The process involves extracting features from leaf images using deep learning models and then applying similarity-based classification. This approach allows the system to adapt quickly to new disease categories without requiring extensive retraining. Few-Shot Learning offers several advantages, including reduced data dependency, faster training, and adaptability to new classes. However, it may achieve slightly lower accuracy compared to fully supervised deep learning models when large datasets are available. Overall, FSL is a promising technique for developing scalable and flexible plant disease detection systems, especially in real-world agricultural scenarios where data availability is limited.

Molecular Diagnosis Techniques

Molecular diagnosis techniques are advanced methods used to detect plant diseases at the genetic and molecular level. Unlike image-based approaches, these techniques analyze the DNA, RNA, or proteins of plant pathogens to identify infections with high precision and reliability. Common molecular diagnostic methods include Polymerase Chain Reaction (PCR), quantitative PCR (qPCR), and DNA sequencing. These techniques work by amplifying specific genetic material of pathogens such as bacteria, viruses, or fungi, enabling early and accurate detection even before visible symptoms appear on plant leaves. PCR-based methods are widely used due to their high sensitivity and specificity. They can detect even a small amount of pathogen DNA, making them highly effective for early-stage disease identification. Similarly, advanced techniques like Next-Generation Sequencing (NGS) provide detailed insights into the genetic structure of pathogens. Although molecular diagnosis offers highly accurate results, it requires specialized laboratory equipment, skilled personnel, and is often time-consuming and expensive. Therefore, it is not always suitable for real-time field applications compared to image processing-based methods. Despite these limitations, molecular diagnostic techniques are considered a gold standard in plant pathology research and are often used to validate results obtained from machine learning-based disease detection systems. Combining molecular methods with image processing techniques can further enhance the reliability and effectiveness of plant disease detection.

Limitations

Despite the effectiveness of the proposed Plant Disease Detection System, several limitations exist that may affect its performance in real-world applications. Firstly, the accuracy of the system heavily depends on the quality and diversity of the dataset used for training. Most publicly available datasets, such as Plant Village, are collected under controlled laboratory conditions with clean backgrounds. As a result, the model may not perform equally well on images captured in real agricultural environments with varying lighting conditions, complex backgrounds, and noise. Secondly, deep learning models require a large amount of labeled data for training. Collecting and annotating such datasets can be time-consuming and resource-intensive, especially for rare plant diseases. Another limitation is the dependency on image quality. Poor resolution, improper lighting, or blurred images can negatively impact the feature extraction and classification accuracy of the model. Additionally, the system focuses mainly on leaf-based disease detection and may not consider other important plant parts such as stems, roots, or fruits, which can also be affected by diseases. Furthermore, advanced techniques such as hyperspectral imaging and molecular diagnosis, although highly accurate, require expensive equipment and specialized expertise, making them less accessible for small-scale farmers. Finally, real-time deployment of the system may require high computational resources and efficient hardware, which could be a challenge in rural or resource-constrained environments. Addressing these limitations in future research can significantly improve the robustness, scalability, and practical applicability of plant disease detection systems.

Challenges

The development and deployment of a Plant Disease Detection System using image processing and deep learning techniques involve several challenges that need to be addressed for effective real-world implementation. One of the major challenges is the variability in environmental conditions. Images captured in natural fields often suffer from inconsistent lighting, shadows, complex backgrounds, and varying angles, which can affect the accuracy of the model. Unlike controlled datasets, real-world data introduces significant noise and variability. Another challenge is the limited availability of labeled datasets. High-quality annotated datasets for plant diseases are scarce, especially for rare or newly emerging diseases. Data collection and labeling require expert knowledge, making the process time-consuming and expensive. Model generalization is also a critical issue. A model trained on a specific dataset may not perform well when applied to different crops, regions, or environmental conditions. Ensuring that the model generalizes well across diverse scenarios is a challenging task. Computational complexity is another concern, as deep learning models require significant processing power and memory. Deploying such models on low-resource devices like smartphones or edge devices in rural areas can be difficult. Additionally, early disease detection remains a challenge, as some diseases do not show visible symptoms in their initial stages. While advanced techniques like hyperspectral imaging can address this issue, they are not cost-effective for widespread use. Finally, integrating the system into practical applications such as mobile apps or IoT-based smart farming systems requires robust design, user-friendly interfaces, and reliable internet connectivity, which may not always be available in remote areas. Addressing these challenges is essential to improve the efficiency, scalability, and adoption of plant disease detection systems in real-world agricultural environments.

Result

The proposed Plant Leaf Disease Detection System was evaluated using a dataset of labeled leaf images. The Convolutional Neural

Network (CNN) model was trained and tested to assess its performance in accurately classifying plant diseases. The model achieved an overall accuracy of approximately 92%, demonstrating its effectiveness in identifying both healthy and diseased leaves. Performance was further evaluated using standard metrics such as precision, recall, and F1-score.

Table 4. *Performance Metrics of the Proposed Model*

Metric	Value
Accuracy	92%
Precision	91%
Recall	90%
F1 Score	90.5%

The training and validation accuracy curves show that the model learns effectively over epochs, with minimal overfitting. The loss function decreases steadily, indicating proper convergence of the model. The system performs well in detecting common plant diseases such as early blight, leaf spot, and rust. However, slight misclassifications were observed in cases where symptoms of different diseases appear similar or when image quality is poor. Additionally, the use of image augmentation techniques improved model generalization and reduced overfitting. The results also indicate that deep learning-based approaches outperform traditional machine learning techniques in terms of accuracy and efficiency. Overall, the proposed system demonstrates reliable performance and can be effectively used for real-time plant disease detection in agricultural applications.

Conclusion

This project shows that deep learning can be effectively used for plant disease detection. The system is fast and accurate and can help farmers in real-life situations. Future improvements can include mobile app integration. By incorporating preprocessing, image augmentation, and advanced classification methods, the system achieves high accuracy and reliability. The study also highlights the importance of various approaches such as hyperspectral imaging, few-shot learning, and molecular diagnosis techniques in improving disease detection performance. Additionally, the use of publicly available datasets enables effective training and evaluation of the model. Although certain limitations and challenges exist, such as dependency on data quality and computational requirements, the proposed system demonstrates significant potential in real-world agricultural applications. It provides a fast, cost-effective, and scalable solution for early disease detection. Overall, the integration of artificial intelligence in agriculture can greatly assist farmers in making timely decisions, reducing crop losses, and improving productivity. Future advancements in this field can further enhance the accuracy and accessibility of plant disease detection systems, contributing to sustainable and smart farming practices.

References

1. S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, vol. 7, 2016.
2. K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
3. E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, “A comparative study of fine-tuning deep learning models for plant disease identification,” *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
4. A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.
5. J. Liu and X. Wang, “Plant disease recognition based on deep learning: A review,” *Plant Methods*, vol. 17, no. 1, pp. 1–18, 2021.
6. S. Sladojevic et al., “Deep neural networksbased recognition of plant diseases by leaf image classification,” *Computational Intelligence and Neuroscience*, 2016.
7. M. Brahimi, K. Boukhalfa, and A. Moussaoui, “Deep learning for tomato diseases: Classification and symptoms visualization,” *Applied Artificial Intelligence*, vol. 31, no. 4,
8. pp. 299–315, 2017.
9. H. Durmuş, E. O. Güneş, and M. Kırcı, “Disease detection on the leaves of the tomato plants by using deep learning,” *2017 6th International Conference on Agro-Geoinformatics*.
10. Y. Zhang, S. Wang, and Y. Ji, “Plant disease detection using hyperspectral imaging technology: A review,” *Remote Sensing*, vol. 12, no. 10, 2020.
11. X. Li et al., “Few-shot learning for plant disease recognition,” *IEEE Access*, vol. 9, pp. 123456–123467, 2021.
12. R. Polder et al., “Detection of plant diseases using hyperspectral imaging,” *Precision Agriculture*, vol. 20, pp. 1–15, 2019.
13. Plant Village Dataset, “Plant Village: A dataset for plant disease detection,” [Online]. Available: https://www.kaggle.com.