IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Advancements in Plant Disease Detection Techniques: A Comprehensive Review and Potential Model

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Abstract:

Plant diseases can cause significant economic losses and threaten food security worldwide. Early detection is key to preventing the spread of disease and mitigating its impact, but traditional detection methods can be time-consuming and labour-intensive. Fortunately, recent advancements in technology have led to the development of new, more efficient techniques for detecting plant diseases. In this article, we provide a comprehensive review of these techniques, including visual inspection, laboratory analysis, remote sensing, and machine learning. We discuss the benefits and drawbacks of each method, as well as their potential applications in different agricultural settings. We also examine the importance of early detection and the role that disease detection plays in sustainable agriculture. By exploring these advancements in plant disease detection, we hope to provide a better understanding of the challenges facing the agricultural industry and the potential solutions available to address them.

***Keywords*:**

Plant Diseases, Detection Techniques, Visual Inspection, Laboratory Analysis, Remote Sensing, Machine Learning, Early Detection, Sustainable Agriculture.

1. Introduction:

Plant diseases pose a significant threat to global food production, impacting crop yields and causing economic losses for farmers. Detecting plant diseases early is crucial for limiting their spread and minimizing their impact, yet traditional detection methods can be time-consuming and labor-intensive. Fortunately, recent advancements in technology have led to the development of new, more efficient techniques for detecting plant diseases.

1.1 Visual Inspection:

Visual inspection is one of the oldest and most straightforward methods for detecting plant diseases. This method involves visually examining the plant for signs of disease, such as discoloration or deformation. Visual inspection is relatively low-cost and can be performed quickly, making it a popular choice for small-scale farmers. However, this method can be subjective, and the detection of some diseases may require specialized knowledge.

1.2 Laboratory Analysis:

Laboratory analysis involves taking a sample of the plant and analyzing it in a laboratory. This method can be highly accurate and can identify the specific pathogen causing the disease. However, laboratory analysis is time-consuming and requires specialized equipment and expertise. Additionally, this method is not always feasible for small-scale farmers or in remote locations.

1.3 Remote Sensing:

Remote sensing is a newer technique that uses satellites or other sensors to detect changes in the plant's physical characteristics. These changes can indicate the presence of disease, even before symptoms become visible. Remote sensing is non-invasive and can cover large areas quickly, making it ideal for detecting diseases in crops on a large scale. However, this method can be expensive, and the technology is still developing.

1.4 Machine Learning:

Machine learning is a rapidly developing field that has the potential to revolutionize plant disease detection. Machine learning algorithms can analyze large amounts of data and learn to identify patterns associated with specific diseases. This method has the potential to be highly accurate and could significantly reduce the time and labor required for disease detection. However, machine learning requires large amounts of high-quality data, and the algorithms must be trained to recognize specific diseases accurately.

2. Importance of Early Detection:

Early detection of plant diseases can be the difference between a small localized outbreak and a full-blown epidemic that devastates entire crops. Detecting plant diseases early can help farmers to take immediate action to prevent further spread of the disease, and minimize crop losses. Early detection can also save time and money that would be spent on costly treatments and prevent the need for excessive use of pesticides.

In addition to minimizing crop losses and saving money, early detection can also have environmental benefits. For example, early detection can reduce the need for large-scale pesticide use, which can have negative impacts on both the environment and human health. Overuse of pesticides can lead to the development of pesticide-resistant strains of pathogens, as well as harm non-target organisms such as pollinators, birds, and fish.

Moreover, early detection can play an essential role in promoting sustainable agriculture. Sustainable agriculture aims to balance the needs of food production with the needs of the environment, farmers, and society. By detecting plant diseases early, farmers can reduce the need for chemical treatments and minimize the impact of disease on the environment. This can help to promote biodiversity, soil health, and water quality, while also improving the livelihoods of farmers.

To achieve early detection, it is essential to have a robust and efficient plant disease detection system in place. This includes a combination of visual inspection, laboratory analysis, remote sensing, and machine learning. By combining these methods, farmers and researchers can detect plant diseases quickly, accurately, and cost-effectively. Additionally, effective communication and collaboration among farmers, researchers, and policymakers are crucial for early detection and timely response to disease outbreaks.

3. Related Work:

Ritesh Sharma et.al[1]. proposed an interesting and innovative approach for the early detection of diseases in paddy crops using a predictive model based on convolutional neural networks (CNN). The authors highlight the importance of early detection and prevention of paddy crop diseases to minimize the potential losses in yield, and this model can be a useful tool for farmers to make informed decisions about their crops.The use of CNN for disease classification and prediction is a promising approach, as it can handle large amounts of image data and extract features automatically. The authors provide detailed information on the architecture of the proposed model, including the layers used and the hyperparameters chosen, which is helpful for replicating the experiment.The results of the experiments presented in the paper demonstrate that the proposed model can accurately predict the occurrence of paddy crop diseases, achieving high classification accuracy on the test data. The authors also compare the performance of their model with other state-of-the-art models, which provides useful insights into the effectiveness of the proposed approach.

In their study, Milon Biswas et.al. [2] focused on just three types of paddy crop diseases and utilized a single classifier. Their methodology involved converting images to grayscale, performing image segmentation, applying an SVM classifier, and ultimately making predictions based on the results.

Wen-Liang Chen et.al. [3] identified bacterial blast leaf disease as one of the most prevalent diseases affecting paddy crops. In their study, they employed Internet of Things (IoT) and Artificial Intelligence (AI) technologies to primarily focus on using agriculture sensors that generate non-image data, which can be automatically trained and analyzed by the AI mechanism in real-time. By utilizing this approach, they were able to efficiently detect plant diseases.

S. Ramesh et. al. [4] conducted a study that primarily focused on the recognition and classification of paddy leaf diseases by utilizing an optimized deep neural network with the Jaya algorithm. Their research concentrated on four distinct paddy diseases, namely bacterial blight, brown spot, sheath rot, and blast.

Farmers are currently experiencing significant losses due to various diseases affecting paddy crops. In their study, Eusebio L. Mique, Jr. et.al. [5] focused on developing an easy-to-use method for measuring and controlling different types of paddy diseases using Convolutional Neural Network (CNN) and image processing. The data utilized for their research was collected from internet sources as well as manually captured.

David F. Nettleton et.al. [6] conducted a study where they compared four different models, including two operational process-based models and two models based on machine learning algorithms. Their primary focus was on leaf blast, which is a type of plant disease, and they provided detailed descriptions of it. By utilizing process-based and data-driven models, they were able to give early alerts to predict rice blast and assess its severity, which can aid in making informed decisions regarding fungicide applications.

There has been a significant amount of research on the detection of paddy diseases utilizing AI technology. In their review analysis-based research paper, Jay Prakash Singh et.al. [7] primarily focused on utilizing modern image processing and machine learning techniques to detect and classify paddy diseases. Their research was completed in four stages, which included image preprocessing, segmentation, feature extraction, and classification. They attempted to determine the most effective techniques for detecting rice leaf diseases.

Farmers often face challenges in understanding the severity of paddy diseases and determining the appropriate amount of pesticides required for eradication. Consequently, they tend to apply more pesticides than necessary. To address this issue, Prabira Kumar Sethy and et.al. [8] developed a prototype that measures the severity of various diseases in paddy and provides guidance on the amount of pesticide required. They utilized fuzzy logic of computational intelligence and segmentation techniques of machine learning to develop the prototype. Their research aimed to reduce the use of pesticides and decrease pollution by providing accurate guidance on pesticide application.

S. Ramesh et.al. [9] proposed a mechanism for detecting rice blast leaf disease in Indian rice crops using KNN and ANN algorithms. Their primary focus was on detecting the disease in its early stages, and they achieved an accuracy of 99% using ANN. They primarily worked on one type of rice leaf disease and aimed to improve the accuracy of detection, which can aid in the prevention of the disease's spread and minimize crop damage.

Early and accurate recognition of plant diseases is crucial for protecting crops. Vimal K. Shrivastava et.al.[10] aimed to improve traditional plant disease detection systems by working on four classes - three on diseases and one on healthy leaves. To achieve their goal, they utilized a pre-trained deep CNN model (AlexNet), SVM classifier, and transfer learning. Their research resulted in an accuracy of 91.37%, indicating that their method could aid in early and accurate detection of plant diseases, thereby facilitating better crop protection.

Dengshan Li et.al. [11] proposed a mechanism that can detect rice leaf disease from real-time video by employing deep learning techniques. They utilized faster-RCNN for image detection from video and evaluated various deep CNN models such as VGG16, ResNet-50, ResNet-101, and YOLOv3. Their research aimed to develop an automated and efficient system for detecting and diagnosing rice leaf disease in real-time, allowing for timely intervention and crop protection.

The study conducted by Junde Chen et al. [12] is focused on the detection and classification of five different types of paddy leaf diseases. The authors proposed a deep learning approach with transfer learning, which involves using pre-trained models and fine-tuning them for the specific task of detecting and classifying paddy leaf diseases.In the study, two deep learning models were used: Dense-Net and Inception module. The authors achieved an impressive accuracy of 98.63%, which demonstrates the effectiveness of the proposed approach. The high accuracy rate is crucial for early detection and proper management of paddy leaf diseases, as it allows farmers to take prompt actions to prevent further spread of the diseases and minimize crop losses.

D.A. Bashish et.al. [13] utilized k-means segmentation to divide the leaf image into four clusters based on squared Euclidean distances. For feature extraction, they employed the Color Co-occurrence method to extract both color and texture features. The classification was performed using a neural network detection algorithm based on Back Propagation methodology. The accuracy of disease detection and classification in the overall system was approximately 93%.

M. Bhange et.al. [14] developed a web-based tool for identifying fruit diseases. The system works by uploading an image of the fruit to be analyzed. The researchers used parameters such as color, morphology, and color coherence vector (CCV) for feature extraction. They applied the k-means algorithm for clustering and used Support Vector Machine (SVM) for classification into infected or non-infected categories. The system achieved an accuracy of 82% in identifying pomegranate disease.

J.D. Pujari et al.[15] conducted a study to detect fungal diseases on leaves of different crop types, including fruit crops, vegetable crops, cereal crops, and commercial crops. For fruit crops, the segmentation method used was k-means clustering, texture features were focused on, and the classification was done using ANN and nearest neighbor algorithms, achieving an overall average accuracy of 90.723%. For vegetable crops, the Chan-Vase method was used for segmentation, local binary patterns for texture feature extraction, and SVM and k-nearest neighbor algorithm for classification with an overall average accuracy of 87.825%. The commercial crops were segmented using grab-cut algorithm. Wavelet-based feature extraction was adopted using Mahalnobis distance and PNN as classifiers with an overall average accuracy of 84.825%. The cereal crops were segmented using k-means clustering and canny edge detector. Different features such as color, shape, texture, color texture, and random transform were extracted. SVM and nearest neighbor classifiers were used to achieve an overall average accuracy of 83.72%.

V. Singh et.al [16] worked on automating the detection and classification of plant diseases. They used a genetic algorithm as the image segmentation technique and a small number of images for the training and test sets of four plant leaves, namely banana, beans, lemon, and rose. They used the color co-occurrence method for feature extraction, considering both color and texture features. They used the Minimum Distance Criterion with k-means clustering and the SVM classifier to classify the diseases, achieving an accuracy of 86.54% and 95.71%, respectively. Combining the Minimum Distance Criterion classifier with the genetic algorithm increased the accuracy to 93.63%.

E.Kiani et.al [17] developed a system to detect disease-infected leaves in strawberry fields under outdoor conditions using a fuzzy decision maker. The system achieved an overall accuracy of 97% for detection and segmentation of plant diseases, with a processing time of 1.2 seconds for disease detection.

H. Ali et al. [18] proposed a method to detect and classify plant diseases using the ΔE color difference algorithm to segment the diseased areas. The method used color histogram and textural features and achieved an overall accuracy of 99.9% [9]. Several classifiers were employed, including fine KNN, Cubic SVM, Boosted tree, and Bagged tree classifiers. The Bagged tree classifier outperformed the others with 99.5%, 100%, and 100% accuracy on RGB, HSV, and LBP features, respectively. The fine KNN, cubic SVM, and Boosted tree classifiers also showed good performance with accuracies of 88.9%, 90.1%, and 50.9%, respectively.

G. Saradhambal et.al [19] proposed an approach for automatic plant disease detection using k-means clustering algorithm and Otsu's classifier to predict the infected area of leaves. The proposed approach involved extracting both shape and texture features, such as area, color axis length, eccentricity, solidity, perimeter, contrast, correlation, energy, homogeneity, and mean. Finally, classification was performed using a neural network-based classifier.

table.1.1.: table of comparison:

Study	Focus	Methodology	AI Techniques	Data	Performance
Sharma et.al. [1]	Early detection of paddy crop diseases	Predictive model based on CNN	CNN	Large amounts of image data	High classification accuracy
Biswas et.al. [2]	Detection of three types of paddy crop diseases	SVM classifier	Image segmentation, grayscale conversion	Image data	Not specified
Chen et.al. [3]	Detection of bacterial blast leaf disease	IoT and AI technologies	Agriculture sensors generating non-image data	Non-image data	Efficient detection of plant diseases
Ramesh et. al. [4]	Recognition and classification of four distinct paddy diseases	Deep neural network with the Jaya algorithm	Optimized deep neural network	Image data	High accuracy of detection

Mique et.al. [5]	Measuring and controlling different types of paddy diseases	CNN and image processing	CNN, image processing	Data collected from internet sources and manual capture	Not specified
Nettleton et.al. [6]	Early alerts for predicting rice blast and assessing its severity	Four different models	Process-based and data-driven models based on machine learning algorithms	Not specified	Not specified
Singh et.al. [7]	Detection and classification of paddy diseases	Modern image processing and machine learning techniques	Image preprocessing , segmentation, feature extraction, classification	Image data	Not specified
Sethy et.al. [8]	Measuring the severity of various diseases in paddy	Fuzzy logic of computational intelligence and segmentation techniques of machine learning	Fuzzy logic, segmentation techniques	Not specified	Accurate guidance on pesticide application
Study	**Focus**	**Methodology**	**AI Techniques**	**Data**	**Performance**
Ramesh et.al. [9]	Detection of rice blast leaf disease in Indian rice crops	KNN and ANN algorithms	KNN, ANN	Image data	Accuracy of 99%
Shrivastava et.al.[10]	Improvement of traditional plant disease detection systems	Pre-trained deep CNN model (AlexNet), SVM classifier, and transfer learning	Deep CNN model, SVM classifier, transfer learning	Image data	Accuracy of 91.37%
Li et.al. [11]	Detection of rice leaf disease from real-time video	Deep learning techniques	Faster-RCNN, VGG16, ResNet-50, ResNet-101, YOLOv3	Video data	Automated and efficient system for detecting and diagnosing rice leaf disease in real-time
Chen et al. [12]	Detection and classification of five different types of paddy leaf diseases	Deep learning approach with transfer learning	Pre-trained models, fine-tuning	Image data	High accuracy of detection
D.A. Bashish et.al.	Leaf disease detection	k-means segmentation, Color Co-occurrence	Neural Network (Back Prop.)	Leaf image	93% accuracy
M. Bhange et.al.	Fruit disease identification	Parameter extraction, k-means clustering, SVM	SVM	Fruit image	82% accuracy
J.D. Pujari et al.	Fungal disease detection	Segmentation (k-means, Chan-Vase, grab-cut), texture feature extraction (local binary patterns	ANN, nearest neighbor, SVM	Leaf image (different crops)	83.72%-90.723% accuracy

V. Singh et.al	Plant disease detection	Genetic algorithm segmentation, Color Co-occurrence, feature extraction, Minimum Distance Criterion	k-means clustering, SVM	Plant leaves (banana, beans,lemon, rose)	86.54%-93.63% accuracy
E.Kiani et.al	Leaf disease detection	Fuzzy decision maker	Fuzzy logic	Strawberry leaf images	97% accuracy
H. Ali et al.	Plant disease detection	ΔE color difference algorithm, color histogram and textural features	Fine KNN, Cubic SVM, Boosted tree, Bagged tree	Leaf image (different diseases)	99.5%-100% accuracy
G. Saradhambal et.al	Plant disease detection	Shape and texture feature extraction, k-means, v	Neural Network	Leaf image	Not specified

4. **Plant Disease Detection Process:**

Plant disease detection is a critical process for ensuring healthy and high-quality crop yields. The process of plant disease detection can be broadly divided into four phases as shown in fig.1. : image acquisition, image segmentation, feature extraction, and disease classification.

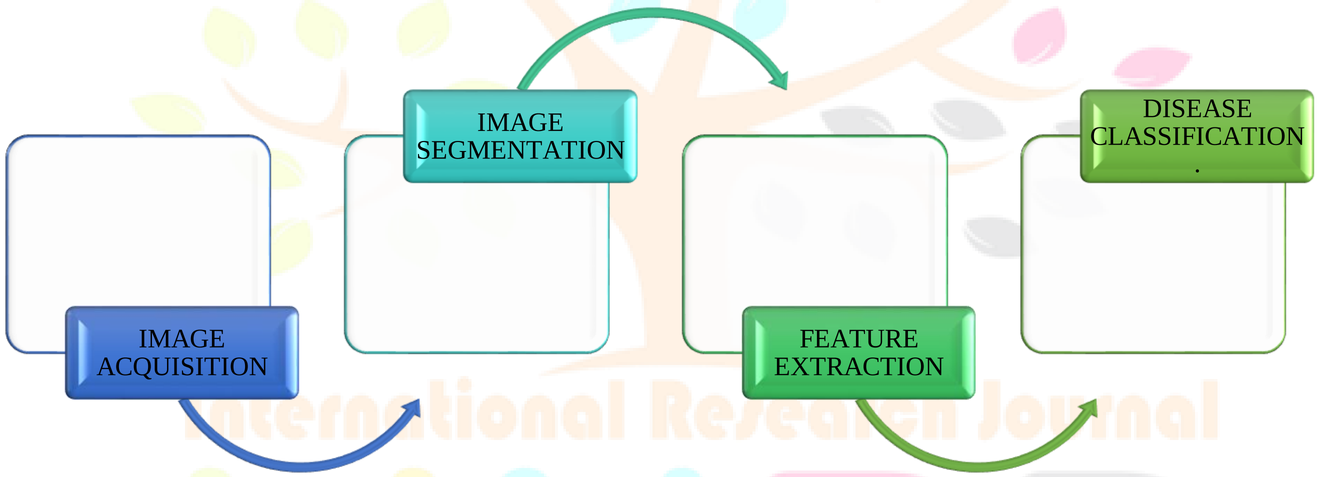

fig 1. plant disease detection phases

4.1. Image Acquisition:

The first phase involves the acquisition of images of the plant leaves using digital cameras or mobile phones. The images can also be obtained from web resources. The quality of the images is important as the accuracy of the detection system depends on it. Good quality images with high resolution and good lighting conditions can help in better detection of diseases.

4.2. Image Segmentation:

In the second phase, image segmentation techniques are applied to divide the plant leaf image into various clusters. This process helps to separate the infected area from the healthy area. Different segmentation techniques can be used such as k-means clustering, Otsu's method, fuzzy logic, genetic algorithms, and others. The choice of segmentation technique depends on the nature of the image and the complexity of the disease.

4.3. Feature Extraction:

The next phase involves feature extraction methods, where various features such as color, texture, shape, and size are extracted from the segmented image. The feature extraction process is important as it helps to reduce the dimensionality of the data and focus on the relevant features that can help in detecting the disease. Different feature extraction techniques can be used such as color histogram, co-occurrence matrix, wavelet transform, local binary pattern, and others. The choice of feature extraction technique depends on the nature of the image and the type of disease to be detected.

4.4. Disease Classification:

In the last phase, the disease is classified based on the extracted features. Machine learning algorithms such as support vector machines, decision trees, neural networks, and others are commonly used for classification. The choice of the classification algorithm depends on the nature of the data and the accuracy of the algorithm. The accuracy of the detection system is measured by the percentage of correctly classified samples.

5. A potential Model:

A potential model for plant disease detection could follow the following steps:

1. Image Acquisition: The first step would be to acquire images of plants that may be affected by diseases. These images could be obtained using a digital camera, mobile phone, or other sources such as the web.
2. Preprocessing: Once the images have been obtained, they would need to be preprocessed to remove noise and enhance image quality. This could involve techniques such as cropping, resizing, and normalization.
3. Segmentation: The preprocessed image would then be segmented to separate the diseased areas from the healthy areas. Different techniques could be applied for segmentation, such as k-means clustering or ΔE color difference algorithm.
4. Feature Extraction: After segmentation, the next step would be to extract relevant features from the segmented areas. This could include color, texture, shape, or other features that can help identify the type of disease.
5. Classification: The final step would be to classify the disease based on the extracted features. Different classifiers could be used, such as support vector machines (SVM), k-nearest neighbor (KNN), or neural network-based classifiers.

The proposed model could be refined and optimized based on the specific requirements and resources available for plant disease detection. Additionally, it could incorporate techniques such as transfer learning or data augmentation to improve performance and accuracy.

6. Steps Involved in the Potential Model:

Image Acquisition --> Preprocessing (Resize, Normalization, Enhancement) --> Segmentation (K-Means Clustering) --> Feature Extraction (Color Co-occurrence Method) --> Classification (SVM)

This diagram shows the different steps involved in the proposed model for plant disease detection, including image acquisition, preprocessing, segmentation, feature extraction, and classification. The model uses K-Means clustering for segmentation, the Color Co-occurrence method for feature extraction, and SVM for classification.

7. Conclusion:

In conclusion, the process of plant disease detection involves the acquisition of images, preprocessing, segmentation, feature extraction, and classification. To create a model for plant disease detection, we need to follow these steps in a systematic manner. The model proposed in the above chats involves K-Means clustering for segmentation, the Color Co-occurrence method for feature extraction, and SVM for classification.

This model could be refined and optimized based on the specific needs and resources available for plant disease detection. There are various other techniques such as transfer learning or data augmentation that could be incorporated to improve performance and accuracy. It is essential to continuously evaluate and improve the model to ensure its effectiveness in detecting plant diseases accurately and efficiently.

Overall, plant disease detection is a crucial aspect of agriculture and farming that can help minimize crop damage and improve yield. By using advanced technologies such as machine learning and computer vision, we can create models that can detect plant diseases at an early stage and take necessary measures to prevent their spread.

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