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Plant Disease Detection Using Digital Image Processing: Opportunities and Challenges

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ABSTRACT

Diseases in plants affect the yield of the plant itself. Agriculture is essential in human life, and if plant conditions are left unchecked, it will result in crop failure, which can affect the economy. Many researchers have developed methods to detect plant diseases, ranging from expert systems to deep learning algorithms. Machine learning is particularly effective for this task as it relies on datasets composed of plant images, making image processing crucial for the identification process. This article reviews the current literature and identifies several research gaps, opportunities, and challenges that must be addressed. Specifically, the article outlines potential avenues for future research in detecting plant diseases using image processing techniques. A significant opportunity exists to develop more effective algorithmic models for detecting plant diseases.

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1. INTRODUCTION

Agricultural products are part of everyday human life. Humans in big cities or villages need agrarian products to meet their daily needs [1]. When viewed from the extent of agricultural land in the world, the world population needs agricultural products for survival [2]. The growing number of plant diseases, which pose a severe danger to global food security, is one of the things that the farming industry fears [3]. The Food and Agriculture Organization (FAO) forecasts that the global population will rise to 9.1 billion by 2050. Consequently, agricultural production must increase by up to 70% to adequately meet the food demands of this expanding population.

Agroecosystems have been negatively impacted by the extensive use of pesticides, fungicides, and nematicides to treat plant diseases [4]. Plant diseases account for a 10-16% loss in the world's crop annually or the equivalent of a cost of US$220 billion [5][4][6][7]. Plant diseases can pose a threat to the productivity and quality of agricultural output [8][9] [10].

Plant disease is characterized as a condition of a plant's local or systemic aberrant physiological function brought on by ongoing and persistent irritation from phytopathogenic organisms (abiotic or biotic) [11][12][13]. Plant diseases impact all plants' existence, development, and production, affecting how healthy and safe human life is. This has happened since humans started practicing agriculture more than 6000 years ago [14]. Identifying plant diseases is one of agriculture's most basic and essential activities [15]. Numerous studies have demonstrated the value of early plant disease detection in order to enhance agricultural output [16].

The importance of accurately diagnosing plant diseases equals that of the challenge [17]. Although human vision can identify and interpret patterns and assess plant diseases, errors can lead to disease identification [15][18]. Based on their knowledge and experience, professionals have been able to detect plant illnesses with the naked eye for a very long time. However, finding a plant disease expert was time-consuming and expensive [19][20]. Modern methods for detecting plant diseases now include image processing, data mining-based classification algorithms, machine learning, and deep learning. These advanced techniques are more time-efficient compared to earlier approaches, offering faster and more accurate detection capabilities [21][22][23][24][25]. The existence of these methods can help farmers improve crop quality, as well as reduce disease incidence with early Detection and timely treatment [26]. This article's primary goals are to evaluate the research literature on plant disease detection using digital image processing, to identify research problems, and to give a general overview of potential future study areas.

2. METHOD

This study used a literature review methodology to examine previous studies on the use of digital image processing techniques for plant disease diagnosis. The literature review process consisted of the following stages [26], [27]:

1. Identification of Relevant Literature: The initial step involved searching for relevant literature across academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search was guided by keywords such as "plant disease detection," "image processing," "machine learning," and "deep learning." Key papers were identified based on their relevance to the topic, publication within the last decade, and contributions to plant disease detection. To make sure the evaluation included the most recent developments in the subject, the search was restricted to articles that had been published within the last ten years. Numerous articles were found in the first search, which were then sorted according to how relevant they were to the subject.
2. Screening and Selection: The next step involved screening the identified literature based on specific inclusion and exclusion criteria. Studies were included if they provided empirical data, proposed new methodologies, or discussed significant advancements in plant disease detection using image processing. Theoretical studies without empirical validation or focused on unrelated topics were excluded. This step ensured that only relevant and high-quality studies were reviewed.
3. Data Extraction and Synthesis: For each selected study, key information was extracted, including the methodologies used, data sets, results, and conclusions. The data extraction process aimed to identify common trends, challenges, and opportunities in the field. The synthesis involved comparing different approaches to highlight their strengths, limitations, and areas needing further research.
4. Identification of Gaps and Opportunities: Finally, the reviewed literature was analyzed to identify gaps in the existing research and potential opportunities for future studies. Particular attention was paid to the challenges of dealing with diverse environmental conditions, the complexity of image data, and the need for more generalized algorithms capable of accurate plant disease detection in real-world scenarios.

3. RESULT AND DISCUSSION

3.1. Plant Disease

The environment that impedes or affects a plant's ability to perform its essential tasks is the cause of plant disease [28]. Plant illnesses are grouped according to the type of the causative agent and the relationship between each parasite to create the relevant symptoms of the plant-pathogen interaction. Abiotic disorders are those caused by non-living ecological factors, whereas biological diseases are those caused by living creatures [29][30]. Nematodes, bacteria, viruses, plague, and fungi are the primary factors in the development of biotic illnesses [14].

- Fungal diseases

Fungi cause the majority of illnesses caused by vegetables. Plants become infected by fungi when their cells are killed, which stresses the plant. A fungal infection can come from various sources, including contaminated seeds, inappropriate soil, crop residues, neighboring plants, and weeds. In addition to standing water, where the fungus is spread chiefly, infected soil, animals, people, equipment, tools, seeds, and other plant material can also spread the disease [31][32].

- Bacterial disease
  Bacteria can spread to the plant's stems, leaves, and roots, among other areas. In other cases, bacteria might even impact the plant's interior without causing any obvious exterior symptoms. Plant infections manifest as wilting, leaf spots, overgrowth, scabs, and cancer. Most of these infections occur internally, making it challenging to diagnose them correctly later on. Bacterially infected plants can potentially infect neighboring plants, rapidly dispersing the illness [31].
- Virus diseases
  Virus infections on plant leaves are the hardest to diagnose. Most viruses are invisible and only partially visible. Mixing up viral infections with nutritional shortages and pesticide damage is typical. Numerous common vectors, including aphids, leafhoppers, whiteflies, cucumber beetles, and insects, can transmit viruses swiftly [31].
- Nematode Disease
  Roundworms, active, thin, or unsegmented, are parasitic nematodes that live on plants (also called nemas or eelworms). Because they are so tiny and translucent, most cannot be seen with the human eye. The majority of mature forms are between 0.25 and 2 millimeters long. Nematode diseases affect 1,200 different plant species. Most of their species inhabit the earth and prey on tiny roots, but others also inhabit and eat bulbs, buds, stems leaves, or flowers. [31][33].

3.2. Plant Disease Detection Method

Algorithms and processes are used in digital image processing for tasks such as picture augmentation, compression, analysis, mapping, and georeferencing [34]. Digital photographs have a significant impact on contemporary society. Pattern recognition, computer vision, industrial automation, and the healthcare industry are a few critical application areas [35]. The use of image-based techniques is thought to be a viable strategy for diagnosing illnesses [36][37][38]. Agriculture's use of suitable image processing to identify and categorize plant diseases is crucial [2]. The steps in Fig. 1 represent a generic division of the image categorization process:

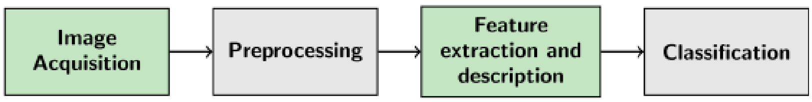

Figure 1. General steps of the image-based plant classification process [34]

The stages of Figure 1 are as follows:

- Image Acquisition
  This stage seeks to capture an image of the complete plant or some of its organs to analyze the subsequent procedure. [39].
- Preprocessing
  Image preprocessing tries to enhance image data to reduce undesired distortion and make existing picture attributes more pertinent for subsequent processing. The preprocessing subprocess takes the image as input and outputs a changed image that is appropriate for the feature extraction step that comes after. Picture denoising, image content augmentation, and segmentation are frequently included in preprocessing. These can be used simultaneously or separately and repeated numerous times until the image quality is acceptable. [40][41] [42]
- Feature Extraction and Description
  The measurement of a potentially segmented and significant portion in the image, whether geometrically or otherwise, is referred to as feature extraction. A list of numbers that define a

particular plant characteristic or plant organ shown in the image is used to describe features (descriptor)[43][44].

- Classification
  All retrieved features are concatenated into a feature vector in the classification step, which is subsequently classified. [41][45].

3.3. Related Research

Recently, a variety of methods have been employed to identify leaf disease. According to Mohanty et al., the issue raised in this study includes developing smartphone features, HD cameras, and high-performance CPUs that can assist in automatic plant detection. [27]. The strategy proposed in this study incorporates both transfer learning and training from scratch, utilizing deep learning architectures such as AlexNet and GoogleNet as the primary training mechanisms. The datasets used in the research consist of 54,306 images of plant leaves, categorized into 38 class labels. These images were processed in color, grayscale, and with leaf segmentation to ensure a diverse and effective training and testing distribution. The data was split with an 80% training and 20% testing ratio. The study successfully identified 26 infections across 14 different plant species, with each class label representing a pair of plant diseases.

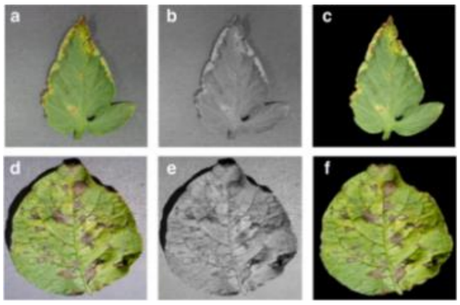

Figure 2. Examples of three distinct versions of the PlantVillage data collection utilized in various experimental setups. Color (a and d), gray (b and e), and segmented leaves (C and f) [27]

Ferentinos [46], suggests that agronomists could greatly benefit from an automated computational system designed to identify and diagnose plant diseases by analyzing images of diseased plant leaves. This study models a Convolutional Neural Network (CNN) using deep learning techniques to accurately recognize and diagnose plant illnesses based on simple images of both healthy and diseased plants. The model was trained on an extensive dataset comprising 87,848 images, representing 25 different plant species across 58 classes of various plant-disease combinations, including healthy plants. Among the various models trained, the most successful architecture achieved a remarkable accuracy of 99.53% in correctly identifying the specific plant-disease combination. Figure 3 provides an example of the image classification process used in the study..

Figure 3. True (green and yellow rectangles) and false (blue rectangles) are two test image classifications that serve as an example (red rectangles)[46].

According to research by Khan et al. [47], demonstrated that contrast stretching significantly enhances the visual quality of input images, which in turn aids in the segmentation process. Their proposed approach improves overall classification accuracy by integrating five primary phases: preprocessing, segmentation, feature extraction and fusion, feature selection, and classification, to effectively identify plant diseases. They employed a technique based on quartile deviations to segment infected areas, generating binary images that were then combined using the coefficient of correlation (CoC). The subsequent level of analysis utilized the New Entropy And Rank-Based Correlation (EaRbC) Framework. Finally, the selected features were classified using a Multi-Class Support Vector Machine (MC-SVM). The approach was tested using the PlantVillage dataset, achieving an average segmentation accuracy of 93.74% and a classification accuracy of 97.7%. Figure 4 depicts the research's framework.

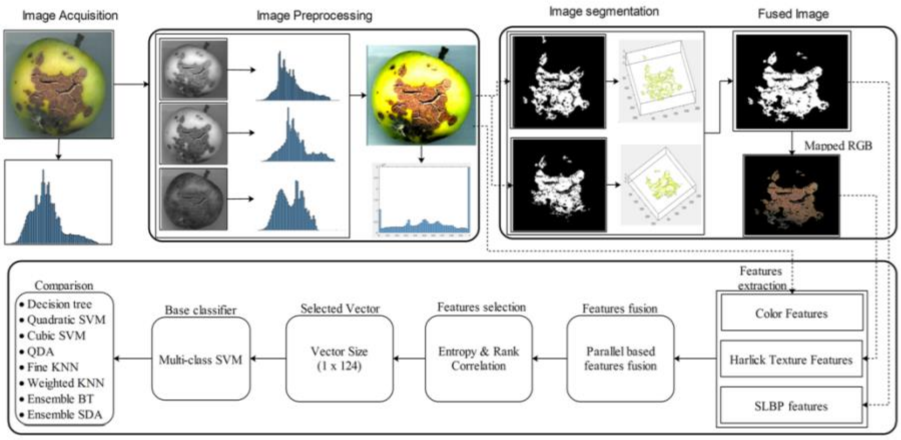

Figure 4. Detection and categorization framework for illnesses in plants and fruits [47]

Hamdani et al. [48] introduced a technique for differentiating between healthy and diseased oil palm leaves. The method involves segmenting the leaf area using K-Means Clustering. Within the segmented region, 41 features were extracted, including color features from RGB (Red, Green, and Blue), Lab (Lightness, a, and b), and HSV (Hue, Saturation, Value) color spaces. Feature selection was conducted using Principal Component Analysis (PCA) based on a color histogram. These selected features were then fed into an Artificial Neural Network (ANN) classifier for disease identification. The effectiveness of the proposed method was evaluated using a dataset of 300 images, comprising 150 healthy and 150 infected leaves. Figure 5 illustrates the key steps of the proposed technique.

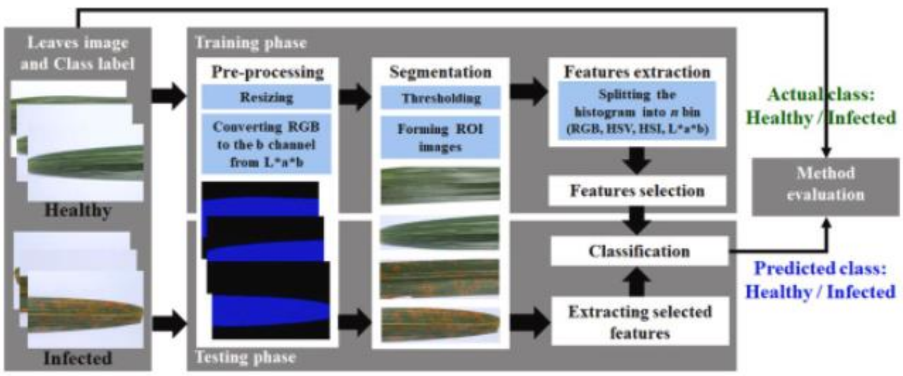

Figure 5. The critical steps in the suggested technique [48]

In their article, Ali et al. [49] It has been suggested that the DeltaE technique can be used to detect citrus fruit illnesses. The suggested method divides disease-affected areas using the E color difference algorithm. In addition, textural characteristics and color histograms are employed to categorize illnesses. K-nearest neighbor (KNN) and Cubic Support Vector Machine are examples of the employed classifiers (SVM). Ninety-nine images of diseased leaves and 100 images of healthy leaves were created using training data from 199 photographs of citrus leaves.

Sharif et al. [50] A hybrid method for detecting and categorizing citrus diseases was put forth by the author in his article. There are two primary stages to the suggested methodology. They are finding lesions on citrus fruit and leaf tissue (A). Numerous citrus illnesses (B). Segmentation was used to obtain Citrus Lesion Spots. Then, a codebook is created by combining the geometry, texture, and color components. The best characteristics are then chosen using a hybrid characteristic selection approach that combines covariance based on skewness, entropy vector, and Principal Components Analysis (PCA) estimate. The Multi-Class Support Vector Machine (M-SVM) was used to classify citrus illnesses based on the preferred attributes. The self-collected picture, aggregated, and citrus disease image datasets all show classification accuracy of 97%, 89%, and 90.4%, respectively, for the suggested method. The system architecture for identifying and categorizing plant diseases is shown in Figure 6.

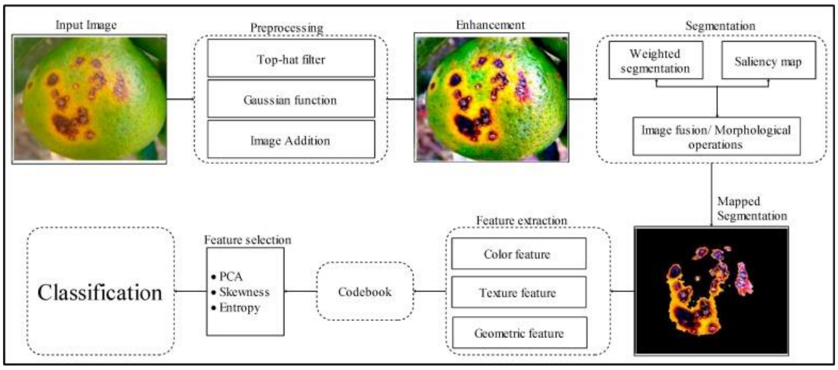

Figure 6. System design for identifying and categorizing plant diseases [50]

Barbedo et al. [17] noted in their study that there is still a substantial gap between what the existing image-based plant disease diagnostic method can do and what is needed. Despite advancements in this domain, most techniques are still insufficiently reliable in identifying different plant species and illnesses. This article suggests a method for diagnosing diseases based on classification, color transformation, and color histogram. The dataset utilized to evaluate their effectiveness consists of 82 photos of 12 different plant species with a range of biotic and abiotic symptoms. The general layout of the suggested method for symptom analysis is shown in Figure 7. The algorithm is broken down into three main sections: primary processing, training (done just once), and core, as can be seen.

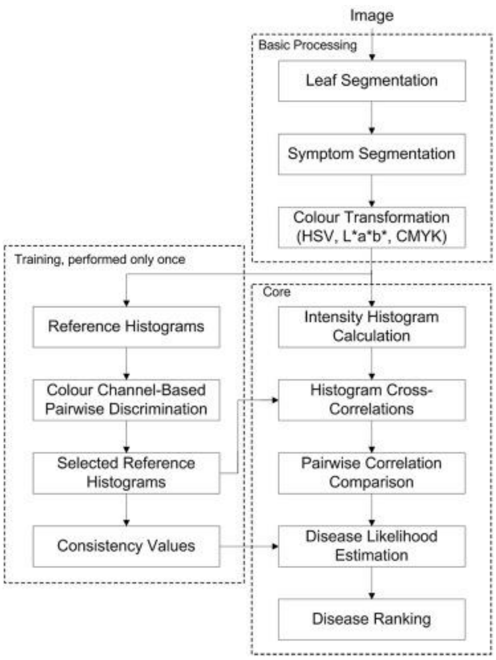

Figure 7. The algorithm is designed for digital image processing-based plant disease detection [17].

Pantazi et al. [51] proposed a classifier aimed at detecting plant diseases such as Black Rot, Powdery Mildew, and Downy Mildew in vines, as well as identifying healthy plants. The proposed approach utilizes Local Binary Patterns (LBP) combined with One-Class Support Vector Machines (OCSVM) for effective classification. A 95% success rate was achieved after 44 of the 46 plant disease combinations tested could be correctly identified. In recent years, CNN's performance in picture categorization and object recognition has improved significantly [52][53][54][55][56]. Data constraints and significant noise in field-grown plants are effectively managed using CNN. Cropped photos of Northern Leaf Blight (NLB) lesions are fed into multiple CNNs trained to classify them to detect and categorize sick images. Figure 8 shows the procedures.

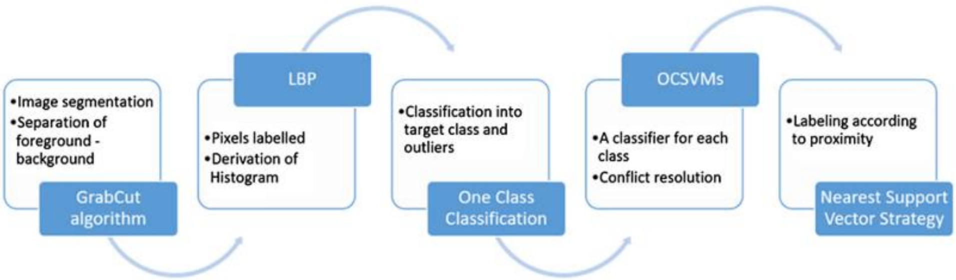

Figure 8. Steps used [51]

Abbas et al. [57] proposed using C-GAN synthetic images and the Transfer Learning approach. The suggested method is divided into two stages: previously trained Pre-Trained DenseNet121 models and synthetic pictures produced using C-GAN for augmentation data. Sixteen thousand twelve images of tomato leaves from Plantviilage's dataset were used. The dataset is broken up into training, validation, and testing datasets, each of which has had its photos downsized to 224x224 for speedier computation. The process is shown in Figure 9. From the several existing studies, it can be seen in the comparison in Table 1.

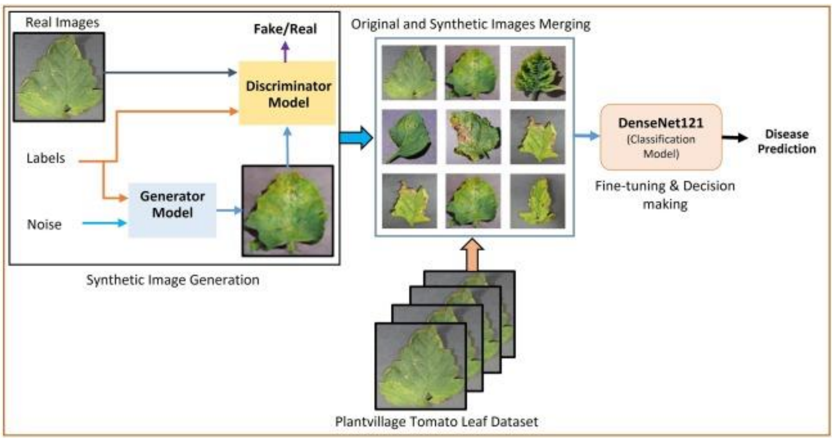

Figure 9. The proposed block diagram [57]

Table 1. Comparison of methods

Article	Methode	Limitation	Advantage
Mohanty et al. [27]	Deep Learning, CNN	The model's accuracy significantly decreased by up to 31% when evaluated on a batch of photos collected under different circumstances than those used for training.	The model's accuracy reaches 99.35% on the training data.
Ferentinos [46]	Deep Learning	In real-world scenarios with limited data, there is a notable decrease in model performance, with reductions ranging from 25% to 35%.	Based on this performance, CNN is well-suited for using straightforward leaf image analysis.

Article	Methode	Limitation	Advantage
Khan et al. [47]	Pattern Recognition (PR) and Machine Learning (ML)	complexity and irregularity of images on plants.	A novel disease classification and detection method are implemented based on the combination of Novel Adaptive Thresholding and Q.d-based segmentation.
Hamdani et al. [48]	Feature Extraction, ANN	An error occurred wherein infected leaves were misclassified as healthy leaves.	The suggested technique yields effective results. The high scores of sensitivity, specificity, and accuracy—99.3%, 100%, and 99.67%, respectively—indicate
Ali et al. [49]	DeltaE, KNN, Cubic SVM	The training data used is still small	Methodologies that are suggested can be used to identify illness in another plant.
Sharif et al., [50]	PCA, M-SVM	Contrast stretching is essential in the case of low-contrast lesion locations because it influences the precision of lesion segmentation and reduces classification precision.	The results indicate that the preprocessing technique significantly improves the contrast of lesion regions, thereby enhancing segmentation precision. Across all datasets used, the average segmentation accuracy achieved is 92.435%.
Barbedo et al., [17]	Transformasi warna, histogram warna dan klasifikasi	How to take pictures that need to be considered, such as avoiding reflections of light/shadows	When new conditions are presented, algorithms may readily be retrained to treat the new conditions.
Pantazi et al., [51]	LBP dan OCSVM	Weakness is in the image resolution	strong generalizability as demonstrated by tests on a variety of leaf samples from diverse plant species
Abbas et al., [57]	Deep Learning (C-GAN, A DenseNet121)	The existing datasets for tomato plant diseases typically lack a sufficient number of images captured under diverse conditions, which is essential for developing high-accuracy models.	The suggested data augmentation strategy enhances the network's generalizability and guards against over-fitting issues. The accuracy of the proposed model for the 5-class, 7-class, and 10-class classification tasks on the original PlantVillage dataset is 98.16%, 95.08%, and 94.34%; for the same tasks on the PlantVillage dataset with synthetic photos, the accuracy is 99.51%, 98.65%, and 97.11%.

3.4 *Opportunities And Challenges*

A review of several studies regarding the detection of plant diseases has revealed challenges and opportunities for further research. There are still opportunities that can be taken to Detect plant diseases. Opportunities and challenges that can be taken in research on plant disease detection are

- Find a method to reduce the complexity and irregularity of the image on the crop.
- It is finding methods and algorithms to improve accuracy in classifying plant diseases.
- Determine the appropriate preprocessing, feature extraction, and classification techniques for the Detection of plant diseases
- Establish suitable methods for monitoring larger-scale farms.
- Using more varied training data in various real situations with different conditions.
- Use a high-resolution image.
- Find disease detection methods in diseases caused by viruses or bacteria and others.

4. CONCLUSION

This article provides a literature review of plant disease identification techniques and a summary of image management, a valuable method for plant disease detection, and current opportunities and challenges for plant disease detection using Digital Image Processing techniques. The work that can be done in the future starts with different testing types of plant datasets in various environments. Developing more efficient methods or algorithms and automated systems for the early Detection of plant diseases can be expanded to identify all possible conditions in plants or focus on one type. Fungi, viruses, bacteria, or nematodes cause plants and various diseases in these plants.

Future research should focus on expanding the applicability and robustness of plant disease detection systems in real-world environments. This includes testing and validating models across diverse and varied datasets that represent different environmental conditions, such as lighting variations, background complexities, and plant species diversity. Additionally, there is a need for developing more efficient algorithms that can handle the complexity and variability of real-world image data. These algorithms should be adept at precisely detecting and diagnosing a broad spectrum of plant

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diseases, including those caused by fungi, viruses, bacteria, and nematodes. Additionally, future research should investigate the incorporation of advanced machine learning approaches, such as transfer learning and data augmentation, to improve the adaptability and generalization of detection models. Automated systems that facilitate early disease detection through real-time monitoring and analysis should also be prioritized to improve agricultural productivity and prevent large-scale crop failures.

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