Comprehensive survey of automated plant leaf disease identification techniques: advancements, challenges, and future directions

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Article Info

Article history:

Received Nov 21, 2023
Revised Feb 26, 2025
Accepted Mar 15, 2025

Keywords:

Convolutional neural network
Deep learning
Global food security
Image processing
Plant leaf disease detection

ABSTRACT

This survey paper extensively researches into the domain of timely plant disease detection, crucial for alleviating agricultural losses and ensuring food security. It accentuates the significance of early identification in efficient disease management and informed agricultural decisions. Conventional manual methods, constrained by labor intensity and subjectivity, pave the way for investigating automated disease detection avenues, prominently leveraging image processing and deep learning techniques. In the subsequent exploration of related work, a panoramic view encompasses an array of methodologies, encompassing neural networks and convolutional neural networks (CNNs), paramount in automated disease detection. The synthesis of image processing intricacies, pre-processing strategies, and feature extraction paradigms alongside deep learning models is meticulously expounded. As the field advances, the paper accentuates lingering challenges in early-stage detection, alongside insightful solutions like data augmentation and sophisticated deep learning models. This survey paper culminates by underlining the dynamic trajectory of automated plant disease identification, accentuating its paramount role in upholding global food security.

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1. INTRODUCTION

The presence of plant diseases has a significant impact on agricultural productivity. Failure to promptly detect plant diseases may lead to an increase in food insecurity [1]. The implementation of effective measures to prevent and control plant diseases is crucial in the management of agricultural productivity. The efficiency of the process is greatly impacted by the early identification of key factors. The identification of plant diseases has emerged as a significant concern in contemporary times. Plants that display symptoms of illness frequently manifest visible markings or lesions on their leaves, stems, flowers, or fruits. Numerous diseases and pest conditions exhibit discernible visual patterns that can be effectively employed for precise identification of abnormalities. The examination of disease symptoms in plants commonly centers on their leaves, which serves as a primary approach for the identification of plant ailments [2]. The practice of identifying diseases and pests that affect fruit trees on-site is a common procedure carried out by agricultural and forestry professionals, as well as by farmers who depend on their own expertise and abilities. The approach described demonstrates subjectivity, requires significant labor, is time-consuming, and has limited effectiveness.

The primary focus within the realm of crop productivity and plant growth pertains to the detection and classification of plant diseases. The timely identification of these diseases allows for the implementation of preventive measures, leading to decreased productivity and financial losses [3]. Achieving optimal crop quality necessitates the implementation of comprehensive disease management and containment strategies throughout the entire farm. The diagnostic process for a disease entails the examination and analysis of symptoms, the identification of the underlying cause, and the implementation of appropriate measures to effectively control its transmission. The following steps are essential for effectively reducing the transmission of infections. Plant diseases have the potential to inflict damage on both the aboveground and below ground parts of a plant [4]. Leaf diseases can be diagnosed through the observation of distinct signs, including the presence of yellow and brown discoloration. To ensure effective disease management, it is crucial to implement preventive measures that safeguard future harvests of rice, wheat, oats, potatoes, tomatoes, and pomegranates from exhibiting these symptoms. Visual observation is a frequently utilized technique by farmers for diagnosing the condition. The previously mentioned approach is recognized for its sluggish performance and restricted reliability within the agricultural sector. Farmers have the option to seek consultation from specialists in order to obtain an accurate diagnosis of the ailment. The implementation of automated techniques enables accurate disease identification, thereby reducing the reliance on skilled labor and leading to cost savings for farmers [5].

Disease occurs in the plant when the causative agent consistently disrupts its normal physiological processes. The plant experiences disruptions in its regular structure, development, function, or other activities due to the presence of an abnormal physiological process. Characteristic diseases or symptoms arise due to disturbances in one or more vital physiological or biochemical systems within a plant. Plant diseases can be categorized based on the infectious or non-infectious attributes of their primary causative agent [6]. Plant diseases can result in substantial damage to plants by impeding various essential processes. This category includes various activities such as photosynthesis, flower and fruit growth and development, overall plant growth, as well as cell division and enlargement. Additionally, they have the ability to disrupt the functionality of the mechanism responsible for the absorption and transportation of nutrients and water [7]. Plant diseases can occur as a result of the presence of diverse organisms, including fungi, bacteria, phytoplasma, viruses, viroids, nematodes, and similar entities. Bacterial pathogens serve as the etiological factors behind various diseases, such as bacterial spot, bacterial blight, bacterial wilt, scab, rot, and similar ailments. Aphids, grey mold, downy mildew, powdery mildew, cylindrocladium, mealybugs, mosaic, spotted wilt, and curly top represent a range of fungal-induced diseases. Each plant exhibits unique characteristics that enable us to identify the underlying cause of a disease, be it a bacterial, fungal, or viral infection. The symptoms of a disease are employed to facilitate the identification of the specific ailment and its root cause [2]. A range of deep learning techniques can be utilized for the purpose of identifying and categorizing different types of leaf diseases. The application of these techniques enables the categorization of various diseases, such as bacterial spots, early and late blights, mold, septoria leaf spots, spider mites, two-spotted spider mites, target spots, mosaic viruses, yellow curl viruses, and healthy leaves [8].

In recent years, extensive research has been undertaken to explore the automated identification of plant diseases. The acquisition of precise and reliable quantitative data is of utmost importance in the diagnosis of plant diseases [9]. The study, conducted by researchers in [10] aimed to examine the diseases that commonly afflict tomatoes and potatoes, with a particular emphasis on assessing the influence of viruses on these crops. The authors conducted a comprehensive analysis of various articles pertaining to the classification of rice diseases in this study. The review conducted an assessment on various factors, such as the dataset used, disease classifications, preprocessing and segmentation techniques, and the type of classifier employed. The authors conducted an analysis of the factors to improve the understanding of the existing literature on the classification of rice diseases. A study was conducted by [11] to investigate the application of machine learning techniques for classifying diseases that impact cotton plants. The study conducted by [12] entailed an examination of disease classification in citrus plants through the utilization of image processing techniques. The objective of the study conducted to examine the classification and identification of plant diseases through the utilization of leaf images. The research outlined in references is based on tailored features. In order to classify illnesses based on manual features, it is necessary to perform a sequence of steps that involve pre-processing, segmentation, and feature extraction on the images. However, this procedure can be characterized as both labor-intensive and time-consuming.

The prioritization of establishing a highly effective approach for detecting signs of illness is crucial, and this objective can be accomplished by utilizing scientific expertise and data. The initial step entails gathering photographs of the leaves from the tomato and potato crops. Photographs can be obtained by utilizing either a high-resolution smartphone camera or a conventional digital camera. The tomato and potato leaves that have been gathered are subsequently subjected to image processing. The process of identifying plant diseases involves the application of various image processing techniques. The process encompasses several techniques, namely capture, pre-processing, restoration, segmentation, augmentation, feature extraction, and classification [13]. The color conversion technique is employed during the preprocessing phase to convert RGB photographs into grayscale images. After removing different types of noise, a set of contrast enhancement techniques is employed to enhance the contrast of the images.

The application of deep learning in the agricultural industry has been limited and relatively new. The method described in reference [14] has proven to be effective in the identification of plant diseases. The study conducted by the authors have focused on the utilization of deep learning techniques for the purpose of plant disease diagnosis. The main focus of their study centered on the data sources, models, and pre-processing methods utilized in the proposed convolutional neural network (CNN) models.

The occurrence of plant diseases poses a significant threat to agricultural productivity, potentially leading to food uncertainty. Early and accurate detection of these diseases is essential for effective disease management, informed decision-making, and prevention of economic losses. However, traditional methods of plant disease identification, primarily relying on manual observation and expert intervention, are subjective, time-consuming, and labor-intensive. These limitations hinder the timely and precise identification of plant diseases, making it challenging to implement preventive measures and control strategies. Additionally, the diverse nature of plant diseases, caused by various agents such as bacteria, fungi, viruses, and further complicates the identification process. Therefore, there is an underlying need for advanced automated techniques that can swiftly and accurately detect plant diseases, leveraging technologies such as deep learning and image processing. This problem statement seeks to address the limitations of existing methods and explore innovative solutions to enable early, efficient, and reliable plant disease detection, contributing to sustainable agricultural practices and food security.

2. RELATED WORK

Based on the findings of [15], specific algorithms for segmentation and feature extraction can be employed to detect plant diseases from images of leaves. Detecting plant diseases manually is a highly challenging task due to the lengthy learning curve, extensive effort, and time requirements involved. The author has divided the process of detecting plant leaf illnesses into five distinct steps: image capture, preprocessing, segmentation, feature extraction, and disease classification. The RGB leaf picture underwent transformation using a framework during the process of image capture. Following this step, the image undergoes pre-processing in order to minimize noise and enhance contrast. Segmentation is a process that involves the division of an image into distinct feature portions using various techniques such as k-means clustering, Otsu filters, and other similar methods. Following the extraction of features from the segmented picture, various classification approaches are utilized to generate the ultimate classification. Plant diseases can be accurately identified using this method.

The utilization of feed forward back propagation has been implemented in [16]. A neural network-based approach is proposed for the identification and categorization of illnesses in grape leaves. The diagnosis involved the utilization of grape leaf images featuring intricate backgrounds. Anisotropic diffusion is applied to the image in order to further eliminate noise. Subsequently, the image is subjected to k-means clustering for further segmentation. The classification of Downey Mildew and Anthracnose watermelon leaf diseases has been accomplished in [17] through the utilization of a neural network-based approach. The author has evaluated the efficacy of the proposed concept by assessing its rates of true positive, true negative, and overall accuracy. The categorization is determined by extracting the color feature from the detected pixels in the region of interest, using the RGB color model. The utilization of pattern recognition methods has been proposed in [18] as a means to identify and categorize infections caused by Alternaria, Myrothecium, and bacterial blight on cotton leaves. The dataset comprises images that were gathered within the premises of the Central Institute of Cotton Research located in Nagpur. The isolation of sick areas is achieved through the utilization of an active contour-based segmentation technique. The author has provided a number of feature recommendations for various crops, such as wheat, orange, citrus, and maize, which are based on a common principle.

A deep learning method was utilized to categorize illnesses in bean leaves. To optimize training durations, enhance accuracy, and simplify retraining, the model was trained using the MobileNetV2 [19] architecture in a controlled environment. One significant advancement in the field of artificial intelligence pertaining to object detection is the utilization of a neural network. The study employed YOLOv3 [20]–[23] to detect and classify six rice leaf diseases, namely blast, bacterial leaf blight, brown spot, narrow brown spot, bacterial leaf streak, and rice ragged stunt viral disease. The accuracy achieved in this classification task was 79.19%. In their study, [6], [24]–[26] introduced a two-layer CNN model. This model was designed to effectively combine multiple layers in order to extract valuable and distinct information from citrus fruits and leaves. The model effectively differentiated between healthy fruits and leaves, as well as those exhibiting common citrus diseases such as melanose, black spots, canker, scab, and greening. The proposed approach by [27] involves the utilization of a hybrid deep learning model. This model aims to reduce the quantity of training process parameters while simultaneously enhancing computation accuracy. This is achieved by combining the advantageous characteristics of dense networks and deep residual networks. In this study, [28]–[31] a suggested model is a deep convolutional neural network (DCNN). By replacing the conventional convolution layers with deeper separable convolutions, it is possible to reduce the number of model parameters and decrease the iteration time. The integration of local binary pattern (LBP) features, which efficiently capture local information for enhancing deep features, is performed.

In a study conducted by [32]–[34], a technique was proposed for the detection of diseases in tea leaves. This approach leverages a modified DCNN. The study employed various developed/modified deep learning architectures to effectively identify and categorize plant diseases. The document provided a comprehensive explanation of the utilization of deep learning models for the representation of various plant diseases. The document lacks a comprehensive analysis of disease early detection methods and the process of identifying and categorizing plant illnesses through the examination of minute samples. Deep learning has been incorporated into various applications, such as crop variety detection and classification, plant identification and classification, and fruit picture grading. The popularity of images captured using mobile cameras or camera devices integrated into robots has been steadily increasing [35], [36].

Rashid *et al.* [37] proposed a novel algorithm based on CNN and image pre-processing to effectively identify and differentiate rice diseases. The algorithm leverages a dataset of 500 authentic photographs captured from the rice empirical field. The suggested model demonstrates improved accuracy compared to the typical machine learning model due to several factors. These include the utilization of the 10-fold cross-validation method, which enhances feasibility and economy. Additionally, the suggested model exhibits a quicker convergence rate and improved identification ability. A novel disease detection model for automatic disease diagnosis was developed using the 4-fold cross-validation method. The model utilized 800 cucumber leaf photos captured by digital cameras. To improve accuracy, the model employed CNN methods with image pre-processing techniques [38].

To enhance precision and obtain a viable solution, a novel model named integrated neural architecture for real-time single shot multibox detector (INAR-SSD) was introduced in [39]–[41]. This model was implemented within the caffe framework, specifically in Google's Inception structure, and utilized rainbow concatenation on the graphics processing unit (GPU) platform. The proposed model employs DCNN to perform real-time disease detection on apple leaves. The dataset used for training and evaluation consists of 26,377 images of apple leaf diseases, comprising a combination of laboratory-generated images and complex images captured in real field conditions. The smartphone application dCrop was developed to forecast crop diseases in modern agriculture. It utilized a public dataset consisting of 54,306 plant leaf photos and employed deep learning-based techniques including AlexNet, ResNet-50, and ResNet-34. These techniques were used to achieve accurate predictions. In addition, a PyTorch model that has undergone training was converted into a TensorFlow pb file. This file was then integrated into the dCrop application, enabling real-time predictions for crop diseases. In a study conducted by [42], [43], a CNN model with a transfer learning approach was employed to detect crop illnesses and identify pests using leaf photos sourced from the PlantVillage database. The implementation of this method resulted in a decrease in both time and human labor requirements, while simultaneously improving accuracy.

A total of 500 tomato leaf photos from the PlantVilliage dataset were utilized in this study to detect and classify 500 instances of leaf illnesses. This was achieved by employing a CNN model in conjunction with the learning vector quantization (LVQ) technique. Furthermore, the utilization of different convolutional filters was implemented to enhance the level of recognition in the classification methodology. The update was created by [44]–[47]. In order to detect leaf spot diseases in sugar beet, an imaging-based expert system is employed. This system utilizes a faster R-CNN architecture with adjustable parameters of a CNN model. The primary objectives of this approach are to achieve optimal accuracy, reduce processing time, and minimize human error. The system analyzes a dataset consisting of 155 images to accomplish these goals [48]. To address the challenges of identifying rice illnesses and resolving issues such as blurring picture edges, noise, significant background interference, and low detection accuracy, proposed the utilization of the k-means clustering technique and the quicker R-CNN fusion algorithm. The more efficient 2D-Otsu algorithm was employed to classify the images of rice diseases for obtaining results. Tables 1 and 2 shows the survey table.

2.1. Research gap

Some of the research gaps in this study are as follows: i) limited focus on early detection: many existing studies focus on disease detection, but there's a lack of emphasis on early detection. Early identification is crucial for timely intervention and prevention of extensive crop damage; ii) need for efficient automation: while automation is gaining attention, traditional methods of disease identification remain prevalent. There's a gap in developing more efficient and accurate automated techniques to reduce the reliance on manual and labor-intensive processes; iii) diverse disease classification: plant diseases are caused by various agents, each exhibiting unique symptoms. However, existing research often overlooks the challenges of accurately classifying diseases that may share similar symptoms; iv) integration of deep learning: while deep learning has gained popularity, its application in plant disease detection is still relatively new and limited. There's potential for developing more sophisticated deep learning models tailored to specific crop diseases; v) limited small sample approaches: many studies focus on large datasets, but there's a gap in developing effective detection and classification techniques for diseases based on limited or small sample sizes; and vi) integration of image preprocessing: existing approaches may not fully explore the potential of image preprocessing techniques to enhance disease detection accuracy, particularly in the presence of noise and variations in image quality.

Table 1. Survey of challenges and gaps in plant disease detection and classification

Aspects addressed	Key points	Advantages	Disadvantages
Importance of early detection	Plant diseases negatively impact agricultural production and food security. Timely detection is vital for effective disease management and informed decisions. Early symptoms often manifest on leaves.	Facilitates timely intervention to prevent crop losses. Enables informed decision-making in agriculture.	Not all diseases exhibit early detectable symptoms.
Limitations of manual methods	Traditional methods involve subjective, time-consuming, and labor-intensive processes. Expert identification may be required. Need for efficient and accurate automated techniques.	Automation reduces subjectivity and human error. Enhances efficiency in disease identification.	Automated methods may require complex algorithms.
Classification of plant diseases	Diseases caused by various agents like bacteria, fungi, viruses, and more. Each disease presents unique symptoms and patterns. Symptoms used to identify specific diseases and their causes.	Allows targeted treatment based on disease agent. Patterns aid in accurate diagnosis.	Certain diseases may share similar symptoms.

Table 2. Literature survey

Study	Approach and findings	Advantages	Disadvantages
[3]	Discusses segmentation and feature extraction algorithms for plant disease detection. Proposes a five-step process for identification, including image acquisition, preprocessing, segmentation, feature extraction, and classification.	Systematic approach for efficient disease identification. Utilizes established image processing techniques.	Process complexity due to multiple steps. May require parameter tuning.
[4]	Utilizes neural networks for grape leaf disease diagnosis and classification. Employs anisotropic diffusion and k-means clustering for image preprocessing and segmentation.	Neural networks offer powerful pattern recognition capabilities. Automation minimizes human intervention.	Neural network training requires significant computational resources.
[5]	Implements neural network-based system for watermelon leaf disease classification. Focuses on color feature extraction and evaluates classification accuracy.	Automation speeds up disease classification process. Color features aid in identifying specific diseases.	Accuracy can be affected by varying lighting conditions and image quality.
[6]	Introduces a DCNN model with deeper separable convolutions for reduced parameters and iteration time. Combines deep features with LBP features for enhanced accuracy.	Deeper separable convolutions reduce model complexity. LBP enhances local information capture.	Model architecture complexity might impact training time.

3. CONCLUSION

In conclusion, this survey has provided a comprehensive overview of the critical role that automated disease detection plays in the realm of agriculture. The detrimental impact of undetected plant diseases on agricultural productivity and food security underscores the urgency of adopting efficient and accurate identification methods. The juxtaposition of traditional manual approaches with advanced image processing and deep learning techniques highlights the transformative potential of automation. The survey of related work showcases the diverse methodologies, particularly neural networks and CNNs, that are reshaping disease detection. The integration of image processing intricacies, pre-processing techniques, and feature extraction mechanisms with deep learning models has emerged as a promising avenue for achieving accurate and timely identification. Despite the strides made, the challenge of early-stage disease detection remains, warranting further research and innovative solutions. As technology continues to evolve, the insights presented in this survey emphasize the continuous need to harness automation for plant disease detection, contributing significantly to global agricultural sustainability and food security.

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, we extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Datasets utilized in this research are cited in reference [1], [36], [44].

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