A survey on plant leaf disease identification and classification by various machine-learning technique

Premakumari Pujar[1,2], Ashutosh Kumar[2], Vineet Kumar[2]
[1]Department of Electronics and Communication, Research Scholar, Institute of Engineering and Technology, Srinivasa University, Mangalore, India
[2]Planet I Technologies, Bangalore, India

Article Info

Article history:

Received Mar 30, 2023
Revised Oct 18, 2023
Accepted Nov 11, 2023

Keywords:

Agriculture
Computer Vision
Image processing
Planets leaves
Plant disease

ABSTRACT

An overview of methods for identifying plants diseases is given in this article. Each sample is categorized by being divided into various groups. The approach of classification involves identifying healthy and diseased leaves based on morphological traits including texture, color, shape, and pattern, among others. Sorting and categorizing plants can be challenging, especially when doing so across a large area, due to the closeness of their visual qualities. There are several methods based on computer vision and image processing. Selecting the right categorization method can be difficult because the outcomes rely on the data you supply. There are several applications for the categorization of plant leaf diseases in fields like agriculture and biological research. This article gives a summary of several approaches currently in use for identifying and categorizing leaf diseases, as well as their benefits and drawbacks. These approaches include preprocessing methods, feature extraction and selection methods, datasets employed, classifiers, and performance metrics.

Corresponding Author:

Premakumari Pujar
Department of Electronics and Communication Engineering, Research Scholar, Institute of Engineering and Technology, Srinivasa University
Mangalore, India
Email: prema.k032023@gmail.com

1. INTRODUCTION

Numerous factors, including the decline in pollinators [1], climate change [2], and plant diseases [3], present a significant threat to global food security. Plant diseases pose a particular danger to the world's food supply, as smallholder farmers rely on agriculture for their livelihoods and productive harvests. With a projected global population of 9.7 billion by 2050, food security will become a paramount concern. To address these challenges effectively, there is a pressing need for swift and accurate methods of identifying plant diseases. The evolution of image processing and artificial intelligence provides a promising avenue to advance agricultural research. Within the realm of deep learning, deep neural networks play a crucial role in categorizing data, analyzing patterns, and extracting essential features [4]. Algorithms for object recognition and picture classification have been successfully applied in several industries, including networking, agriculture, business, the automotive sector, and communications [5]–[8]. Traditional approaches to diagnosing plant diseases in agriculture rely on visual inspections conducted by experts, often followed by extensive laboratory analysis. This process is not only time-consuming but also inaccessible to smallholder farmers. To address this challenge, researchers have evaluated the efficacy of intelligent and automated disease detection systems that harness artificial intelligence, deep learning, and machine learning techniques. The primary objective of deep learning algorithms is to extract features from images, which are then employed, as needed, for various classification or regression tasks. The classifier will have access to a bigger pool of descriptive qualities if the features gathered by several deep-learning techniques are merged. The main cause of this drastic decrease in agricultural productivity is plant diseases. Visual examination of pathogenic indicators and identification of symptom aspects are two traditional methods for determining the severity of an illness. The specialized knowledge that can only be attained via significant research and study is needed to recognize and evaluate the severity of the disease [9]. To address forthcoming agricultural trends and get over production development roadblocks, creative solutions are still needed. Existing techniques must be changed, and new ones must be created, to create an autonomous plant disease detection system that performs better than visual inspection. Environmental factors have an impact on all stages of plant growth (temperature, rainfall, climatic change, and light).

A plant's leaves are thought to be its most crucial part. A few of the many factors that cause leaves to deteriorate and eventually suffer damage include inadequate nutrition, diseases, pests, insufficient sunshine, and floods. The growth of plants is influenced by several important elements, one of which is disease-induced leaf damage. Diseases severely impair several plant processes, including transpiration, photosynthesis, germination, and pollination. Thus, one of the most important tasks for raising agricultural output is the early detection of leaf (foliar) illness. Bacteria, fungi, and viruses are the major pathogens responsible for disease [10].

Scientists and farmers must engage in challenging tasks, such as boosting agricultural production and generating high-quality food items, to fulfil the rising global demand. Thus, it is essential to progressively boost agricultural output and exploration. Thus, Sandhu and Kaur argue that the adoption of new technologies is essential for generating large and beneficial contributions. Using these strategies, it may be feasible to reduce expenditures and errors while also developing farming practices that are lucrative and helpful to the environment. Before a disease is properly discovered, a farmer may spend money, time, and effort attempting to determine its origin [11]. After a disease has been recognized, the proper illness management choices may be chosen. To handle this issue, a swift and exact technology that can quickly and reliably identify the sickness present on the leaf is sought. Procedures such as visual identification need considerable work for a full visual examination of a big agricultural region. An image is preprocessed to emphasize the special characteristics of a certain leaf species. The image is then segmented so that the items of interest may be distinguished from the backdrop. Utilizing chromatic, morphological, textural, and structural characteristics, feature extraction identifies the leaf's essential characteristics.

Identifying plant diseases for the sake of visualization is incredibly time-consuming, inaccurate, and unreliable. Yet, implementing an automated detection method minimizes labour and enhances precision. Yet, there are a few problems with the literature-based automatic detection approaches, which will be explored in the next section. Currently, available approaches for improving the quality of images by preprocessing are inefficient. The standard approach for illness diagnosis has several problems, according to the most current study, including increased time complexity, low detection accuracy, higher classification error rates, and inefficient feature extraction. Owing to the ineffectiveness of current image segmentation algorithms, the detection rate has been drastically reduced. For the detection rate of the classifier to rise, a proper segmentation technique is necessary. The difficulty of building classifiers to extract a large number of features and the subsequent reduction in feature size increases the time necessary to identify a disease [12].

2. RELATED WORK

Lu *et al.* [13], a novel method for identifying rice diseases is introduced, leveraging advanced deep convolutional neural networks (CNNs) techniques. The primary aim behind employing the convolutional neural network (CNN) model was to achieve a significantly improved classification rate when compared to conventional methods. To train the CNN model gradient descent algorithm was applied to analyze the structure and parameters. The conventional neural network was applied to identify the rise of diseases. Further CNN model was applied to identify the rice diseases with a higher accuracy ratio. According to Pagariya and Bartere [14], the goal was to detect and address cotton crop diseases using the K-means clustering algorithm. To conduct this study, an Image segmentation technique was employed to process images and extract features for disease detection with the assistance of the K-means clustering algorithm. Machine learning techniques were applied for disease identification, with a specific focus on two primary categories: leaf-related diseases and diseases caused by pests. The results shed light on the advantages of an automation-based approach for identifying crop diseases, particularly in the monitoring of extensive crop fields and the timely detection of disease symptoms.

Warne and Ganorkar [15], a proposed approach focuses on the detection, diagnosis, and timely management of diseases to prevent substantial losses in crop production. The study concentrates on the cotton crop, which is grappling with a critical issue leading to a decline in cotton production. The image preprocessing stage incorporates the application of the histogram equalization technique, enhancing the contrast in low-contrast images. For segmentation and classification tasks, a K-means clustering algorithm is utilized to categorize objects based on their feature sets into K classes. Furthermore, neural networks are employed for classification purposes.

Sarangdhar and Pawar [16], a system is designed and developed with the objective of disease detection and control on cotton leaves, coupled with monitoring soil quality. To conduct this investigation, a Support Vector Machine-based regression system is employed for the identification and classification of five cotton leaf diseases, including Bacterial Blight, Alternaria, Gray Mildew, Cercospora, and Fusarium Wilt. An Android-based mobile application is created to provide information about the diseases and their remedies to farmers. This application displays disease-related data and sensor information, as well as the control of relay switches. The incorporation of Raspberry Pi in conjunction with the android application renders this system cost-effective and self-sufficient.

Sardogan *et al*. [17], a combination of a CNN model and the learning vector quantization (LVQ) algorithm is employed for the detection and classification of tomato leaf diseases. The dataset comprises 500 images of tomato leaves exhibiting four different disease symptoms. The CNN model is designed to automatically extract features and perform classification. Filters are applied to the three-color channels based on the red, green, and blue (RGB) components. The LVQ algorithm utilizes the output feature vector from the convolutional part for network training. Experimental results demonstrate the effectiveness of this method in accurately identifying four distinct types of tomato leaf diseases. Prajwala *et al.* [18], a convolutional neural network model known as LeNet is utilized to detect diseases in tomato leaves. This approach aims to provide a solution for tomato leaf diseases using a simplified method, while keeping resource utilization to a minimum. Neural network models are applied to automatically extract features and classify input images into their respective disease categories. With the proposed model, an average accuracy of 94-95% is achieved, underscoring the viability of the neural network approach.

Prajapati *et al*. [19], a comprehensive survey was conducted on methods for the detection and classification of cotton leaf diseases. Cotton leaf images were captured using a digital camera, and image-processing techniques were employed to eliminate noise and background interference from the leaf images. The features related to color, shape, and texture of the leaves were extracted through image analysis, and machine learning techniques were utilized to classify the diseases. The results obtained underscore the pivotal role played by leaf characteristics in the accurate identification and classification of diseases.

Sibiya and Sumbwanyambe [20], deep learning frameworks were harnessed to detect plant leaf diseases. This study's objective is to identify the most prominent software frameworks used in constructing machine-learning systems for plant leaf disease detection. For meta-analysis purposes, the support vector machines (SVM) technique was also incorporated. Additionally, the study aims to determine the reliability of different deep learning frameworks in image classification and which modules yield the most precise results. Nagaraju and Chawla [21], the significance of deep learning algorithms in crop disease detection is emphasized. This study also explores the utilization of existing neural network techniques for image data processing. The research involves a comparison of results obtained from various deep learning models, highlighting their performance evaluation, particularly in the context of hyperspectral data analysis. Furthermore, the study underscores the valuable role of deep learning techniques in enhancing plant disease detection and system performance, thereby increasing accuracy.

Mohanty *et al*. [22], a dataset comprising 54,306 images of both diseased and healthy plant leaves, collected under controlled conditions from a public dataset, is employed. A deep convolutional neural network is trained to identify crop species and detect diseases or their absence. The model's performance on a held-out test set attains an accuracy rate of 99.35%, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on progressively larger and publicly available image datasets paves the way for widespread, smartphone-assisted crop disease diagnosis on a global scale.

Barbedo [23], an investigation is conducted into the influence of dataset size and diversity on deep learning techniques applied to plant pathology. This study involves the collection of images from 12 different plant species, each presenting various characteristics in terms of sample quantity, disease variety, and environmental conditions. Transfer learning is applied to a pre-trained convolutional neural network (GoogLeNet) using the neural network toolbox available in MATLAB 2017. The selection of GoogLeNet architecture was based on its superior performance in the context of plant disease recognition. The parameters used to train the network viz: base learning rate, momentum, mini batch size, and number of epochs. The results reveal that the use of limited image datasets for training brings many undesirable consequences that still prevent the effective dissemination of this type of technology. Arsenovic *et al*. [24], Marko Arsenovic and colleagues introduced a novel dataset featuring images of leaves captured in real-world settings, showcasing different angles and various weather conditions. This dataset is meticulously labeled for both classification and detection tasks. The dataset's parameters were carefully chosen to enhance the classification accuracy and practical utility of the model. To address the challenge of overfitting, several augmentation techniques were applied. Additionally, a generative adversarial network (GAN) architecture was employed to expand the dataset's size and enhance its content. Furthermore, to facilitate the identification of plant diseases, a two-stage architecture named PlantDiseaseNet was proposed. The architectural design of this novel framework has demonstrated exceptional accuracy, particularly in complex environmental conditions.

Ferentinos [25], multiple convolutional neural network (CNN) models were designed using deep learning methodologies to detect and diagnose plant diseases based on simple leaf images of both healthy and diseased plants. An extensive open database was employed, containing a substantial dataset comprising 87,848 images representing 25 different plant species across 58 distinct classes, encompassing various plant-disease combinations, including healthy plants. These images were used to train the models. The accuracy of several models was compared, with the best-performing model achieving a remarkable 99.53% success rate in identifying the specific plant and its associated disease. Geetharamani and Pandian [26], a novel model for plant leaf disease identification was proposed, utilizing a deep convolutional neural network (DCNN). The model was trained using an open dataset containing diverse classes of plant leaves and background images. Six different data augmentation techniques were applied, including image flipping, gamma correction, noise injection, principal component analysis (PCA) color augmentation, rotation, and scaling. The results demonstrate that data augmentation significantly enhances the model's performance. In terms of classification accuracy, the proposed model outperforms popular transfer learning approaches, achieving a validation accuracy of 96.46%. Furthermore, the proposed model's accuracy surpasses that of traditional machine learning approaches.

Mahlein *et al*. [27], a model based on spectral disease indices is introduced for detecting diseases in sugar beet plants. The researchers explored various state-of-the-art technologies for the identification and diagnosis of different plant leaf diseases. This model utilizes hyperspectral-imaging data to detect three of the most severe leaf diseases in crops: Cercospora leaf spots, sugar beet rot, and powdery mildew. The spectral disease indices model achieves classification accuracy in the range of 85% to 92%. Anjna *et al*. [28], the author explains the methodology employed for plant disease identification. Image segmentation is performed using the K-means classification method, which has yielded favorable results. Feature extraction for categorization is accomplished using a grayscale co-occurrence matrix. The author then conducts a comparative analysis of several categorization techniques, highlighting the effectiveness of decision trees in efficiently organizing data into classes. Additionally, SVM with its kernel function and K-nearest neighbor (KNN) are identified as suitable options for this task, with both demonstrating notable efficiency among the algorithms considered. Singh and Misra [29], a novel genetic algorithm, known as the minimal distance algorithm, is introduced for the purpose of detecting diseased sections of plants and conducting image segmentation. Subsequent to the image segmentation procedure, the author evaluated the algorithm's accuracy by employing a range of classification techniques, including K-means clustering and SVM.

Waghmare *et al.* [30] suggested a methodology for identifying diseases in plants by analyzing leaf textures. A colored image is sent into the system, which is segmented to detect the contaminated zone and a particular piece of the leaf is extracted. A texture-based model is created based on the characteristics. Every new type of leaf disease has a distinct leaf texture. This is the information that the SVM classifier uses to determine the illness. In this study, the author employed a multiclass SVM classifier to categorize and diagnose illness in photos of grape plant leaves. The image pattern is then classed as a multiclass SVM categorization in groups that are either healthy or unwell. The planned research focuses on downy mildew disease and black red, which are two of the most frequent and worst affecting diseases. The recommendation method developed in this paper gives 96.6 percent accurate expert advice to tenants fast.

Maniyath *et al.* [31] provide strategies and procedures for leaf-based disease detection that have proven to be effective. Random forest is the technique used in this suggested study to create a dataset by detecting healthy or sick leaf photos. The suggested work is divided into four phases: dataset identification, feature extraction from leaf images, dataset identification, function extraction, classifier extraction, and classification. The datasets created by infected and stable or healthy leaves are combined and trained using the Random Forest algorithm and grouping of infected and healthy movies. The histogram-oriented gradient (HOG) has been used to extract valuable features from images. In general, using machine learning to train large datasets offers us a straightforward and effective method for detecting numerous plant diseases. The model in this study was trained on papaya leaves using the Random Forest Classifier technique. With a 70 percent accuracy rate, the model can be used to categorize. With a large number of photos and other local and global features, the model’s accuracy can be improved.

Hernández and López [32] expressed serious reservations about forecast uncertainties. Predicting an unknown sample for which the model has not been trained is challenging and uncertain. This can be evaluated by including uncertainty in the prediction. The author proposes that Bayesian deep learning techniques be used to solve this challenge. In this case, the misclassified output can be viewed as a source of uncertainty. The model is trained using a deep convolutional neural network architecture to identify the diseased region. This paper uses three optimization techniques: stochastic gradient descent, stochastic gradient markov chain monte carlo (MCMC), and markov chain (MC) dropout. Out of these three, the MC dropout algorithm and SGD produced overconfident predictions, while SGLD produced less confident predictions, all based on probabilistic entropy. Out of the three, it is the most accurate. The major parameter used to train the deep neural network was image entropy.

Hossain *et al*. [33], introduced a technique based on color and texture for the detection and classification of plant leaf diseases. The proposed system conducts image segmentation and feature extraction by working with color and texture attributes, with the color space being converted to Lab. Analysis and classification of these features are carried out using the KNN classifier. Sharma *et al.* [34], a methodology based on machine learning and image processing is suggested for the categorization of plant leaf diseases. In this experimental approach, images undergo processing through a Gaussian filter, leading to a conversion of the color space from RGB to hue, saturation, and value (HSV). Disease identification is achieved through various classifiers, including logistic regression, KNN, and SVM, while images are segmented using K-means clustering.

Image preprocessing refers to the most fundamental level of picture alteration. Preprocessing seeks to improve picture data by removing undesired disturbances or enhancing a few visual characteristics required for further processing and analysis. A pixel from the image is picked, and its value is reset to the neighborhood average. The approach for image pre-processing is separated into groups based on the pixel neighborhood size, which is used to compute the lighting of a new pixel. To decrease picture noise, several preprocessing strategies, such as cropping the image to the appropriate region, are investigated. Moreover, a smoothing filter is applied to the restored image. The purpose of image enhancement is to improve contrast. The three preprocessing processes are clipping, smoothing, and boosting. Denoising is applicable to a variety of reduction methods. The optimal threshold setting improves the efficacy of the medium filter in the presence of salt-and-pepper noise. In the presence of both salt and pepper, pixels in the light region get darker; while pixels in the dark region become brighter [35] Cropping is the first step in image editing. When a few unnecessary visual components have been eliminated, the area of interest is evaluated. To generate a new brightness value for the output picture, image filtering uses a tiny zone around each input pixel.

Segmenting the image is a vital step in identifying the several distinctive areas of a picture that are important. Each region must adhere to the consistency requirement in a finite number of zones, and these zones cannot overlap. Image segmentation is a common method for classifying the pixels in a picture in a decision-based application. The pixels are astonishingly homogeneous inside each zone and have a striking contrast between them since the image has been separated into several distinct zones. Many applications include pattern recognition, image processing, traffic imaging, and healthcare. Images may be segmented using a variety of methods, including neural network-based, edge-based, threshold-based, and cluster-based methods. Clustering is among the most productive methods. Subtractive clustering, mountain clustering, fuzzy C-means (FCM) clustering, and K-means clustering are other clustering methods. K-means clustering is among the most frequently used clustering techniques. With an initial set of measured data, feature extraction produces acquired values that are pertinent and non-repetitive to assist subsequent learning and generalization procedures. Table 1 give the details of the previously done survey.

Table 1. Survey table

Author	Methodology	Highlights	Limitations
[36]	DoubleGAN	A super-resolution generative adversarial network (SRGAN) was employed to generate corresponding 256x256 pixel images, effectively enhancing the imbalanced dataset.	Segmentation is not carried out
[37]	two pre-trained convolutional neural networks (CNNs), EfficientNetB0, and DenseNet121	The aim is to augment the diversity and quantity of images, allowing the model to effectively grasp more intricate data scenarios.	the large parameter size in the models persist.
[38]	SLIC Segmentation (Simple Linear Iterative Clustering)	Web and mobile applications were created to detect diseased areas on corn leaves, utilizing the most effective deep learning model as the classifier.	identifying diseased regions corresponding to different disease types on individual plant leaves is limited
[39]	convolutional network (RFCN)	To identify plant diseases using the newly created dataset.	plant disease has not been identified in various crops in the complex horticultural environment
[40]	EfficientNetV2	Focused on two diseases affecting cardamom plants, specifically colletotrichum blight and phyllosticta leaf spot, as well as three diseases impacting grape plants: Black Rot, ESCA, and Isariopsis Leaf Spot.	plant disease has not been identified in various crops

2.1. Research gaps

- The implementation frequently produces results that are inaccurate. There needs to be more optimization.
- Segmentation requires priori information.
- A database expansion is required to achieve greater accuracy. There haven't been many illnesses covered. In order to cover additional illnesses, efforts must be expanded.
- The potential factors contributing to misclassifications include variations in disease symptoms among different plants, the need for feature optimization, and a requirement for additional training samples to encompass a wider range of cases and enhance disease prediction accuracy.

3. CONCLUSION

Due to agriculture's significance to India's economy, a large portion of the population works in agricultural, either directly or indirectly. The national economy greatly benefits from agricultural exports. By 2050, there will be 10 billion people on the planet, which means that agricultural productivity must rise by at least 70%. The demand for agricultural goods is increasing along with the global population. Making existing fields more productive is the only option to increase agricultural output because new land cannot be used for farming. In certain regions of India, labor-intensive manual agriculture is still practiced, which is inefficient. In agricultural planting, early disease detection is a challenging but crucial task because, unlike changes in leaf color or texture, early leaf spot is very hard to identify with the naked eye before the illness spread widespread. It is researched to classify plant leaf diseases using computer vision. Here, research is being done to identify several plant-leaf diseases, which will increase agricultural yields when discovered in the earliest phases of development.

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BIOGRAPHIES OF AUTHORS

Premakumari Pujar is currently working as Lecturer at Department of Electronics and Communication Engineering, Government polytechnic Turuvekere Tumkur Karnataka India. She received her B.E and M. Tech. degrees in Electronics and communication Engineering and VLSI design and embedded system from VTU, Belgaum, India in 2004 and 2021 respectively. Her areas of interests include material science, embedded systems and Image processing. She can be contacted at email: prema.k032023@gmail.com.

Ashutosh Kumar is working as a Director at Planet I technologies. He holds a Ph. D degree and his area of interest are artificial intelligence, machine learning and cloud computing. He received B. E. in computer science from MSRIT. He has 20 yeaCLR of working experience is several domains. He can be contacted at email: ashu2k6@gmail.com.

Vineet Kumar is a researcher and expert in the fields of computer vision, deep learning, and AI, has made significant contributions to the development and application of these cutting-edge technologies. Currently, he is technical director at planet I technologies and founder of pyrros technologies. After completing an engineering degree, he embarked on a career in research, focusing on the application of machine learning and AI to solve complex problems in a range of fields. He can be contacted at email: vineet@planetitechnologies.com.