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UNVEILING THE FUTURE OF PLANT LEAF DISEASE DETECTION: AN EXTENSIVE EXAMINATION OF IMAGE PROCESSING METHODS

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ABSTRACT

In this review paper, we have conducted a thorough investigation of prior and contemporary research on the detection of plant leaf diseases. The conventional manual visual inspection for assessing the quality of plants has proven to be inherently unpredictable and inconsistent. Moreover, it necessitates a substantial level of expertise in the realm of plant disease diagnostics, particularly in phytopathology, leading and genetic to disproportionately lengthy processing times. Consequently, there has been a paradigm shift towards utilizing image processing techniques for the identification of plant diseases. This paper is structured into three principal sections. The first section furnishes a comprehensive review of the various algorithms used, wherein we compare significant algorithms and studies that have employed image processing and artificial intelligence techniques. The second section delves into the frameworks and juxtaposes these against earlier research endeavors. Subsequently, we engage in an in-depth discourse concerning the precision of the outcomes achieved. Drawing insights from our review, we offer a detailed exposition of the performance in detecting and classifying illnesses. Lastly, we consolidate the findings and address the challenges encountered in plant leaf disease detection through image processing.

Keywords: Plant Leaf Disease Detection, Image Processing Algorithms, Disease Classification, Precision Assessment, Automated Detection Methods, Feature Extraction, Segmentation Classification.

1. INTRODUCTION

Agriculture in this world has emerged as a significant contributor to a country's overall economic growth, making it the cornerstone of the nation's economic stability. With a substantial share in a country’s Gross Domestic Product (GDP), agriculture remains the primary industry. The resilience and productivity of this sector are vital for the nation's prosperity. However, the vulnerability of crops to diseases poses a significant threat, as crop damage can lead to a considerable reduction in overall agricultural output, ultimately impacting the economy. Leaves, being the most sensitive part of plants, often exhibit the earliest signs of diseases [1]. Hence, from the very inception of a crop's life cycle to its maturation for harvest, vigilant monitoring and swift disease management are paramount. Traditional methods, relying on naked-eye observation by skilled professionals, have been the historical approach to disease monitoring. Nevertheless, this labor-intensive and time-consuming process is gradually being overshadowed by the advent of automated and semi-automated plant leaf disease detection methods. Recent years have witnessed a surge in innovative methodologies aimed at creating autonomous and semi-autonomous systems for the detection of plant leaf diseases. Comparative analyses have demonstrated that these technological advancements outperform the traditional manual observation methods in terms of speed, cost-efficiency, and accuracy. These techniques enable the delineation of disease boundaries, identification of affected leaves and stems, determination of the size and contours of the affected region, and the assessment of the color of the infected area. This paper aims to explore a diverse range of approaches for diagnosing plant diseases, with a focus on the intersection of image processing and disease detection. The subsequent sections of this paper are organized as follows: The first section provides a concise overview of the significance of diagnosing plant diseases within the context of agriculture and economic stability. The subsequent sections delve into background research, recent advancements in the field, algorithmic methodologies, and the corresponding outcomes.

2. LITERATURE REVIEW

Exploring and detecting plant diseases remains a central focus within the domain of machine vision research. This specialized field involves the utilization of machine vision equipment to capture plant images, primarily to ascertain the presence of any diseases [2]. Notably, agriculture has been at the forefront of adopting computer vision technology for the identification of crop diseases, gradually replacing the conventional method of diagnosing plant ailments through visual inspections. Over recent decades, the significance of plants has grown on a global scale. Scientists and technologists have long been intrigued by the potential role of plants in addressing pressing issues, including global

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health, energy production, and beyond. dwindling global plant cover has raised concerns about heightened risks related to global warming associated with the challenges. In response to these concerns, various research initiatives have been launched, equipping scientists with the knowledge required to develop cutting-edge convolutional layer systems, enabling advanced image detection and plant disease classification, incorporating techniques such as LSTM, autoencoders, and GANs. Image detection proves invaluable, particularly in distinguishing between healthy and diseased leaves. This is where convolutional neural networks (CNNs) come into play, augmented by LSTM, autoencoder, and GAN architectures, allowing them to scrutinize plant images and identify potential irregularities within the plant's natural environment. Notably, researchers in this field often draw upon scanned images of both healthy and diseased plants as a benchmark for comparison. Conventional machine learning approaches for plant leaf disease identification predominantly rely on conventional image processing algorithms or handcrafted features and classifiers [3]. When developing an imaging scheme, this technology incorporates a multitude of characteristics related to plant diseases. Furthermore, it meticulously selects optimal light sources and shooting angles to ensure uniform illumination in captured images. These meticulously designed imaging systems can significantly streamline traditional algorithms, albeit often at a higher cost. Nevertheless, there are instances where traditional algorithms may struggle to fully mitigate the effects of environmental variations when operating in natural settings [4]. This is primarily due to the dynamic nature of natural environments, for which these algorithms were not originally designed. The identification and diagnosis of plant leaf diseases in complex, natural ecosystems pose multifaceted challenges, including subtle variations in lesion size and type, limited contrast, significant variations in lesion appearance, and substantial image noise. Additionally, the process of capturing images of crop diseases and pests in natural light environments is susceptible to numerous distractions. It is in such scenarios that the incorporation of advanced techniques like GANs proves advantageous, aiming to improve disease detection outcomes. One category of deep learning models, specifically convolutional neural networks (CNNs), has recently demonstrated substantial success across various computer vision applications, spanning from recognizing facial expressions [5], detecting text scenarios [6], monitoring traffic [7], to identifying medical images [8], among others. Companies, both domestic and international, have leveraged deep learning applications for crop disease detection, yielding practical solutions such as WeChat applets and photo recognition apps. In essence, deep learning-based algorithms for plant disease detection exhibit significance in both academic and practical contexts.

3. METHODOLOGY

This research aims to provide a comprehensive and cutting-edge overview of the state-of-the-art in plant leaf disease detection using image processing. To achieve this objective, we employ a systematic literature review approach. The systematic review involves the methodical identification, analysis, and synthesis of the latest research findings in this rapidly evolving field. This approach ensures that our review is rigorous, transparent, and free from bias, enabling us to offer valuable insights into the current landscape of plant disease detection technology.

4. MODELING AND ANALYSIS

The proposed model is SLR-PLDD (Systematic Literature Review on Plant Leaf Disease Detection). SLR-PLDD is a meticulously structured model designed to conduct a comprehensive and methodical analysis of the latest research in the field of plant leaf disease detection using image processing. This model ensures that the review process is systematic, rigorous, and unbiased, providing valuable insights into the cutting-edge developments in this domain

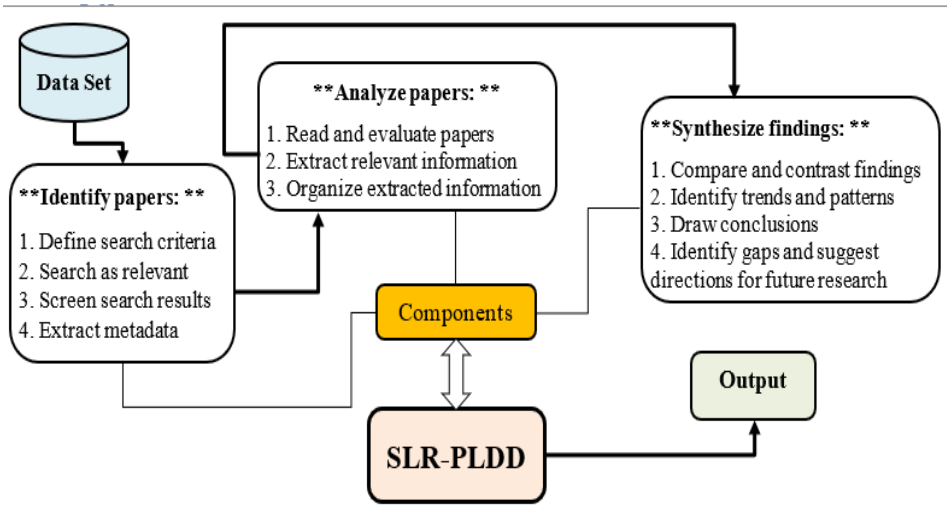

Fig 1: Proposed Model (SLR-PLDD)

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4.1 Algorithm-Centric Review

For ANN, in this research [20], a novel K-means clustering technique was developed to address the issue of noisy photographs of paddy leaves, often distorted by camera lighting. This method effectively removes image noise and proceeds to identify the specific paddy plant disease. The classification technique employed combines Artificial Neural Networks (ANN) and FUZZY logic. The study referenced in [13] utilizes a strategy involving feature extraction and image segmentation. Shape and color properties are recovered using SIFT, followed by an evaluation of results using an ANN classifier. This approach offers an effective means of assessing the overall health of cotton plants. Another approach for evaluating the well-being of cotton plants is presented in [21], involving the acquisition and analysis of leaf images. This method combines multiple image processing techniques with an Artificial Neural Network (ANN) to enable rapid and precise diagnosis of cotton leaf diseases. The authors of [18] introduced a composite feature vector, trained through Machine Learning (ML) methods, specifically an Artificial Neural Network (ANN). Their decision support model integrates machine learning techniques to facilitate the categorization and identification of leafy plants.

In the domain of Soft Computing, a technique incorporating K-means clustering is employed to pinpoint affected leaf tissue [22]. This study harnesses the power of K-Nearest Neighbors (KNN) for the identification of diseased leaves, their classification based on the type of disease, and the presentation of corresponding results. A versatile algorithm is presented in [23], designed to address ailments across the board. This supervised learning algorithm, while agnostic to the specific ailment, serves as a demonstration by accurately detecting gray fungus on cotton plants and evaluating the disease's severity to determine the stage. In the study detailed in [13], a methodology for disease assessment leverages features extraction and image segmentation. The process involves the use of Scale-Invariant Feature Transform (SIFT) to recover shape and color attributes, with subsequent evaluation using a K-Nearest Neighbors (KNN) classifier. The proposal in [14] suggests the development of an image processing system capable of recognizing and categorizing four distinct plant disease forms. The experiment, conducted on a dataset of over 500 images, deploys the K-Nearest Neighbors (KNN) classifier for effective analysis. Introducing a novel Deep Learning approach integrated with an Internet of Things (IoT) strategy for optimal prediction outcomes [24]. The LDEDLP method, powered by cutting-edge innovations like IoT, excels in the efficient detection of plant diseases and timely dissemination of relevant alerts to the appropriate stakeholders.For CNN, the method proposed in [25] categorizes plant leaf disorders into 15 distinct classes, employing a Convolutional Neural Network (CNN). Within these categories, 12 groups represent different plant diseases, such as bacteria and fungi, while the remaining three groups pertain to healthy leaves. Research detailed in [26] demonstrates the application of deep neural networks for the classification of leaf images, forming the foundation of a plant disease identification model. This model efficiently discerns plant leaves from their surroundings and accurately detects 13 different plant diseases amid healthy foliage. The model leverages deep CNN to distinguish between healthy and diseased leaves and maintain consistency with the backdrop images. In a separate investigation [27], authors employ a multi-stage classification process, aiming to enhance prediction accuracy and systematically exclude potential outcomes. This approach is also employed for plant leaf disease identification using Convolutional Neural Networks (CNN). The process involves preprocessing the images, segmenting them using IFFCMC and AO thresholding, extracting GLCM features from the segmented images, and reducing feature dimensions using the PCA technique. Ultimately, a DCNN-based classification is executed. In a study introduced in [9], the practice of gathering leaf photo characteristics through K-means clustering is presented. The algorithms are rigorously tested using data from the training set. Results reveal the exceptional performance of SVM in identifying and categorizing fungal infections on cereal crops. The research paper [10] primarily centers on the segmentation of leaf and fruit images. After retrieving pertinent features, SVM comes into play during both training and classification phases. A computer program proposed in [11] implements five crucial steps, efficiently harnessing SVM and the minimum distance criteria for accurate diagnosis and categorization of examined disorders. This tool proves valuable for farmers who can access a web-based application [12] designed for fruit disease diagnosis. The process includes image downsizing, feature extraction based on criteria like color, morphology, and contrast, and the utilization of SVM for classification. The study described in [13] adopts a methodology involving feature extraction and image segmentation, with the recovery of shape and color properties using SIFT. SVM evaluation follows the feature extraction process. In another research endeavor [14], the suggestion is to develop an image processing system capable of recognizing and categorizing four distinct plant disease forms. This extensive experiment was conducted with a dataset comprising over 500 images, employing the SVM classifier. In [15], the author presents a strategy for detecting and identifying illnesses affecting tomato plants, utilizing the Gabor wavelet transform system to extract relevant image characteristics. The SVM Machines with various kernel functions are employed for classification. Utilizing K-means clustering in the Ycbcr and Lab color spaces for illness component extraction, the study [16] explores SF-CES for the

color images. Further categorization involves the retrieval of GLCM texture features and color texture characteristics, culminating in classification based on SVM. A comprehensive examination of plant disease identification through various approaches is undertaken in [17]. The authors in [18] introduce a composite feature vector designed for training by a Support Vector Machine (SVM). Their decision support model incorporates a range of machine learning techniques for leaf plant categorization and identification. In a different approach [19], the concept of the gray level cooccurrence matrix is utilized for image segmentation and feature extraction. Classification is subsequently carried out using a multi-class support vector machine. GLCM (Gray-Level Co-occurrence Matrix) was applied to extract features in [29], followed by the utilization of a classification technique for the training and testing of plant leaves. This approach exemplified a systematic methodology, employing a random forest as the classifier. In [30], authors explored seven different classifier methods to distinguish and categorize diseased and healthy potato leaves, analyzing over four hundred and fifty photos sourced from publicly available plant village datasets. The accuracy of random forest classifiers outperformed other classification methods. In the domain of deep learning, the Long Short-Term Memory (LSTM) model emerges as a pivotal asset for sequence analysis and prediction tasks. The LSTM architecture is tailored to unravel intricate dependencies and patterns within sequential data, rendering it invaluable for a spectrum of applications, from time series forecasting to natural language processing. LSTM networks excel in circumventing challenges posed by lengthy temporal relationships and mitigating the notorious vanishing gradient issue, often encountered in traditional recurrent neural networks. In parallel, the realm of unsupervised learning unveils the versatile realm of autoencoders. Autoencoders, comprising an encoder and decoder, embark on a transformative journey encompassing dimensionality reduction, noise removal, and feature acquisition. The encoder seamlessly maps input data into a compact, lower-dimensional latent space, while the decoder orchestrates the intricate task of reconstructing the original input from this newfound representation. Autoencoders are the unsung heroes of data simplification, entrusted with roles such as image compression, anomaly identification, and data generation.

4.2 Framework-Centric Review

This study, as detailed in [22], follows a comprehensive, two-phase approach. The initial phase involves image acquisition, followed by image pre-processing in the second phase. Feature extraction is the third stage, which is applied to both the training and testing sets. Subsequently, training is conducted in the fourth stage, with the results extended to the testing set for classification. The concluding step entails recognition. These phases encompass the training and testing segments of the system. The framework is structured around key steps: image acquisition, image pre-processing, image segmentation, feature extraction, and subsequent comparison with a permanent database, leading to disease detection and result display. The author of [29] presents a method that employs image processing for plant disease identification. The proposed framework includes sequential steps, commencing with image acquisition, followed by image pre-processing, image segmentation, feature extraction, and concluding with classification. In another study, as exemplified in [9], the authors adhere to a standard sequence of image processing steps, which includes image capture, picture pre-processing, image segmentation, feature extraction, and classification. A parallel approach is observed in [33], where the method encompasses image acquisition, followed by image selection for segmentation. This segmentation involves two distinct techniques: leaf region segmentation and disease region segmentation, culminating in disease severity assessment. The approach detailed in [10] also adopts a multi-stage strategy, involving training and testing phases. It initiates with image acquisition, followed by image pre-processing and feature extraction. These steps are replicated for both training and testing sets. The training phase is subsequently followed by classification, concluding with recognition. In the study described in [20], various techniques are employed to diagnose paddy diseases. The framework's steps include image acquisition, image preprocessing, image segmentation, feature extraction, and image classification. The authors in [25] introduce a computer vision system for plant leaf disease identification. This system encompasses several phases: image acquisition, image preprocessing, CNN structure design, training, testing, and, ultimately, plant leaf disease detection. In the research discussed in [11], the authors propose a method for the identification and classification of leaf diseases. The suggested framework encompasses several stages, including RGB picture capture, color transformation, pixel masking and removal, RGB mapping, segmentation, extraction of useful segments, computation of texture, and classification. This comprehensive system incorporates image acquisition, pre-processing, image enhancement, color space conversion, segmentation, feature extraction, classification, and disease diagnosis [34]. In [31], the proposed system follows a series of steps, beginning with image acquisition, pre-processing, segmentation, feature extraction, matching content, and concluding with the display of the disease and its corresponding solution. Similarly, in [23], the framework includes sequential steps of image acquisition, pre-processing, segmentation, feature extraction, and classification. Another study, as seen in [26], involved deep CNN training using Caffe, an open-source deep learning framework. The system's phases include data acquisition, image pre-processing and analysis, image segmentation, and

pattern classification [35]. The two phases, the training phase and the testing phase, constitute the framework in [12]. The training phase includes steps such as input image, image pre-processing, feature extraction, clustering, and classification. The testing phase encompasses input image from the user, pre-processing, feature extraction, and classification. In the study detailed in [13], the authors employ common image processing steps, including image acquisition, pre-processing, segmentation, feature extraction, and classification. The proposed methodology in this work [14] leverages image processing techniques, involving stages such as image acquisition, pre-processing, segmentation, feature extraction, and classification. In [21], the authors propose a technique for identifying cotton leaf diseases using artificial neural networks. The framework encompasses key steps, including input image, image pre-processing, feature extraction, and classification. The authors in [36] recommend the use of neural networks for diagnosing and classifying grape leaf diseases. Their proposed framework involves stages like image acquisition, background removal, pre-processing, segmentation, lesion extraction, feature extraction, and classification. In the SVM-based tomato disease detection approach presented in [15], the framework includes four fundamental phases: image acquisition, pre-processing, feature extraction, and classification. In [16], the authors suggest a system using image processing methods to identify unhealthy areas on citrus leaves. The proposed framework includes image analysis and classification stages, encompassing image pre-processing, segmentation, feature extraction, and classification. The study discussed in [17] proposes an image processing technique for plant leaf disease identification. The framework is designed with a multi-layered approach, covering stages like image acquisition, pre-processing, segmentation, feature extraction, and classification. In [37], the authors propose a system for detecting plant infections using image processing. The framework involves several steps, including image acquisition, pre-processing, segmentation, feature extraction, and classification. The authors in [27] introduce a deep neural network-based approach for plant disease detection and classification, featuring a multi-stage classification system. In [18], the authors present a machine learning model, incorporating edge feature extraction, color feature extraction, and texture analysis. The combined feature vector is trained, and the results are classified, including the identification of rice plants and their diseases. The work in [28] suggests automatic feature extraction and plant leaf disease detection using GLCM features and convolutional neural networks. The proposed framework comprises operations like image pre-processing, segmentation, feature extraction, and classification. In [19], the authors recommend using machine learning methodologies to identify and classify diseases in potato plant leaves, employing image segmentation, feature extraction, and classification. In [24], the authors suggest combining deep learning networks with Internet of Things (IoT) techniques for efficient plant leaf disease detection. Their approach involves operations such as image pre-processing, feature extraction, image segmentation, classification, and IoT assistance. In [30], the authors focus on the detection of potato disease using image segmentation and machine learning. Their framework incorporates image processing, image normalization, color space conversion, image segmentation, feature extraction, training, and classification. Figure 1 illustrates the proposed approach.

5. RESULTS AND DISCUSSION

In the study detailed in [22], the outcomes indicate that the system effectively recognized Alfalfa diseases with an accuracy of up to 90%. This achievement was made possible through the application of K-Means Clustering, KNN algorithm, and Local Binary Pattern (LBP). Another approach, as illustrated in [32], categorizes the infection intensity into various percentages, such as 20%, 40%, and 75%. The solution is based on the utilization of the Canny edge detection technique and Gaussian mixture model (GMM). In the research presented in [29], the authors identified plant diseases using image processing techniques, including K-means clustering, Random Forest algorithm, and GLCM. While the accuracy is not mentioned, it's noted that the solution is quite fast. A study found in [9] proposed a system for plant disease identification using image processing techniques. To assess overall precision, accuracy, recall, and F-measure, various techniques were employed. Notably, three of the algorithms achieved an accuracy rate exceeding 90%, with SVM (Polynomial Kernel) providing the highest accuracy at 95.87%. The results from the experiment in [33] achieved an accuracy of 98.60%. This accuracy assessment involved using the simple threshold and triangle thresholding method. The author suggested the utilization of MATLAB for plant disease detection during image processing in [10]. The system is expected to deliver high accuracy, although the specific percentage is not mentioned. This accuracy was achieved using K-means clustering and support vector machine (SVM). In [20], the authors employed image processing techniques, including K-means clustering, ANN, and fuzzy classification, to identify and quantify paddy leaf disease symptoms. While the accuracy is not provided, the solution is described as more accurate. In this paper from [25], a convolutional neural network (CNN) was used, resulting in an excellent accuracy rate of 98%. The authors of the study in [11] proposed a system for detecting unhealthy regions of plant leaves using texture features, achieving an accuracy of 94%. This was accomplished through the use of a support vector machine and Minimum distance criterion. In another study, [34], the authors presented a system for evaluating

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the use of image processing in cotton leaf disease identification. The segmentation was performed using the K-means clustering approach, and classification was carried out using neural networks, resulting in an accuracy of 89.56%. In [31], the authors suggested a method for identifying and classifying plant leaf disease. The accuracy of this study reached 90.98%. In another approach found in [23], two cascaded classifiers were utilized by the authors. Features included local statistical features and hue and luminance from the HSV color space.

The KNN classifier was used, resulting in an accuracy of 82.50%. Additionally, in [26], a novel use of convolutional neural networks (CNN) was introduced by the authors for plant disease recognition. The deep learning framework Caffe was employed, achieving an accuracy of 96.3%. The authors in [35] suggested a method for segmenting images to differentiate between two categories of orchid leaf diseases, achieving an accuracy of 86.36%. A web-based application, proposed by the authors in [12], enables farmers to identify fruit diseases by uploading fruit photos. Using K-means clustering for clustering and Support Vector Machine (SVM) for classification, the system achieved an accuracy of 82%. In the context of paddy leaf disease detection, the authors employed the SVM classifier with different kernels, such as Linear Kernel (95.63%), RBF Kernel (94.23%), and Polynomial Kernel (95.87%) [13]. In a similar study, [14], digital image processing techniques were applied to examine and identify plant leaf diseases. K-means clustering was used for segmentation, while GLCM and LBP were utilized for feature extraction.

Classification involved three types of classifiers: KNN, SVM, and Ensemble, with SVM under the cubic kernel achieving the highest accuracy at 98.2%. In [21], the authors proposed a technique to detect and classify leaf diseases using artificial neural networks, resulting in a moderate accuracy of 80%. In the study found in [36], the authors aimed to identify leaf diseases using artificial neural networks and image processing. Surprisingly, the system achieved a perfect accuracy of 100%. The research in [15] presented a support vector machine-based method for detecting diseases in tomato leaves. The accuracy achieved with the Cauchy kernel was 100%. In contrast, [16] discussed image processing methods for the early detection of plant diseases in citrus leaves, achieving accuracies of 96% using the SVM RBF classifier and 95% using the SVM POLY classifier.

The approach in [17] suggested employing image processing to identify plant leaf disease, achieving an overall recognition rate of 92.4%. In [37], the authors recommended an automatic detection system for infected plants, achieving an accuracy of 98.27%. The study in [27] described a deep learning method for identifying and categorizing plant diseases, attaining an accuracy of 96%. In [18], a decision support for locating illnesses in rice plants was suggested. The machine learning model encompassed three feature extraction techniques, and the accuracy was 92.4% for SVM and 99.5% for ANN. In [28], the authors proposed a framework with several parts, achieving a high accuracy of approximately 97.43%. The authors suggested a methodology for identifying and classifying diseases affecting potato plants in [19], achieving a 95.99% accuracy. To optimize prediction results with precision, a new deep learning technique was introduced in [24], combining deep learning with the Internet of Things (IoT) techniques, resulting in an accuracy level of approximately 99%.

Table 1. Overview of Plant Leaf Disease Detection Algorithms

Paper	CNN	ANN	SVM	KNN	RF	LSTM	Autoencoder	Accuracy
[18]	✓	✓	SVM-92.4%	ANN-99.5%			✓	98.30%
[28]	✓			✓		✓		97.43%
[24]	✓		✓				✓	99%
[30]	✓	✓			✓			97%
[11]	✓		✓			✓		94.74%
[31]				✓				90.98%
[23]	✓		✓		✓		✓	82.50%
[12]	✓							82%
[14]	✓	✓	SVM98.2%	KNN– 80.02%		✓		98.2%
[15]	✓						✓	99.10%
[16]	✓		✓	✓		✓		96%

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Table 2. Plant Leaf Disease Detection Techniques and Results Overview

Paper	Culture	Algorithm	Dataset	Accuracy
[18]	Rice, Potato	SVM, ANN, Autoencoder	120	SVM-92.4%, ANN-99.5%
[28]	14 different crops	IFFCMC, CNN, KNN, LSTM	54206	97.43%
[24]	Different vegetable crops	CNN, SVM, Autoencoder	54300	99%
[30]	Potato	Random Forest, CNN, ANN	450	97%
[11]	30 different crops	SVM, CNN, LSTM	500	94.74%
[23]	Cotton	KNN	140	82.50%
[12]	Pomegranate	K-Mean, SVM,	610	82%
[14]	Chilli, grape, rice, soya bean, wheat, rose, cotton, apple, lichi	KNN, SVM	560	SVM-98.2%, KNN–80.02%
[15]	Tomato	SVM, K Means Clustering	200	99.10%
[16]	Citrus	SVM, K-means, LSTM	200	96%

5.1 Discussion- The timely and accurate detection and classification of plant diseases play a crucial role in supporting crop growth. While diseases can be identified through manual observation and experienced monitoring, these methods are time-consuming and costly. Image processing, on the other hand, offers an effective alternative, where algorithms and digital cameras replace human observation and judgment. Recent advancements in computer vision-based algorithms have shown promise in identifying and categorizing diseases in agricultural and horticultural crops. However, there are some important issues that need to be addressed:

Lack of expertise in image processing techniques: The performance of computer vision systems heavily relies on the choice of image processing techniques and classification strategies. Challenges like handling large datasets and preventing overfitting often arise when evaluating segmentation and classification methods. Authors sometimes omit crucial technical details.

Processing Speed: The speed of disease detection and classification is crucial due to the vast amount of data to be analyzed. Feature extraction and selection methods are employed to reduce data dimensions and facilitate further processing.

Restrictive setup requirements: Environmental conditions, lighting, camera angles, and equipment used for image capture pose challenges for real-world applications. While existing approaches perform well in controlled laboratory settings, their accuracy diminishes in outdoor conditions. Robust calibration is required to mitigate the effects of these variables. Natural lighting conditions also introduce unpredictability due to variations in color.

Data reliability: Inadequate and unverified data information is a significant concern. Authors often fail to provide comprehensive details about the devices and settings used in their experiments, making it challenging to verify results. Transparency in testing and training data is essential.

The need for a universal approach: Creating a single system capable of identifying all types of plant leaf diseases is a challenging task. Many proposed methods are specialized for specific diseases. Therefore, a universal approach to disease identification should be developed.

In conclusion, authors should invest more effort in understanding and mastering the technologies they aim to employ. Some researchers produce high-quality work by clearly outlining their methods, devices, and measurable criteria.

6. CONCLUSION

One notable advantage for farmers lies in the early detection and categorization of plant infections through image processing strategies. This proactive approach enables farmers to prevent the spread of infections to critical leaf areas before they affect neighboring leaves. Plant diseases have been subject to misidentification and misclassification through various methods and frameworks employed by researchers. These diseases, exacerbated by climate change in recent years, significantly contribute to economic losses and post-harvest damage in agriculture. Over time, several effective methods have been developed for the detection, monitoring, and assessment of plant diseases. Traditional approaches involve biochemical and pathological analyses, as well as expert visual interpretation. However, the recent shift toward non-invasive technologies has garnered increased attention. This study provides a comprehensive overview of disease classification techniques for plant disease detection and introduces a photo segmentation method

that holds promise for automating the detection and categorization of plant leaf illnesses. The gathered data on associated plant diseases contributes to delivering precise diagnoses. The proposed algorithm's efficiency in recognizing and categorizing leaf diseases is underscored by its exceptional performance with minimal computational resources. Furthermore, the potential for leveraging other algorithms to enhance classification accuracy is an exciting prospect for future research in this domain.

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