



Plant Disease Identification Using Image Processing: A Systematic Literature Review

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Abstract

This article is a literature review focusing on plant disease identification using image processing techniques. This review aims to provide a comprehensive analysis of dataset sources, preprocessing methodologies, segmentation techniques, feature extraction processes, and various classification methods, along with their associated accuracies. It also discusses challenges encountered and potential future research directions. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, a literature search was conducted in the Scopus database to obtain primary studies. The search covered Scopus-indexed journals and proceedings published by IEEE, Elsevier, Springer, MDPI, and ACM between 2019 and 2025. The initial identification phase yielded 9,286 studies screened. Further screening was performed based on specific eligibility criteria, including relevance to the topic, year of publication, subject area, document type, and articles written in English, resulting in the selection of 82 studies for the review. The findings indicate that the most commonly used dataset is PlantVillage, followed by field data. The dominant preprocessing techniques include image enhancement and augmentation. For segmentation and feature extraction, the most frequently used methods were k-means and CNN, respectively. Sixty-one studies achieved an accuracy exceeding 90%. However, several key challenges remain: data limitations, methodological issues, and practical constraints. Future research should focus on developing more representative datasets, hybrid approaches that integrate classical and deep learning methods, and lightweight, adaptive decision support systems suitable for real-world agricultural applications. This review supports continued progress in this field by providing valuable insights for researchers developing image-based methods for identifying plant diseases.

Keywords: classification method; image processing; plant disease identification; systematic literature review

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1. Introduction

The productivity of agriculture is a vital component for maintaining the global economy. The rise in the number of people worldwide calls for an equivalent advancement in crop production [1]. The Food and Agriculture Organization (FAO) has established an objective of achieving a 70% augmentation in agricultural productivity by the year 2050 [2].

The phenomenon of climate change affects temperature, rainfall patterns, and the frequency of extreme weather events. These changes impact food production and pose a potential threat to global food

security. Variations in temperature and rainfall can disrupt plant growth, water availability, and nutrient cycles, creating opportunities for pests and diseases to develop, which can lead to varying yields and reduced agricultural productivity [3]. According to the FAO, approximately 40 percent of agricultural products worldwide are destroyed by pests and diseases each year [1].

To address this issue, early and accurate identification of plant diseases is essential. This process significantly helps farmers take appropriate actions to prevent the spread of disease. Infected plants typically exhibit signs

or lesions on their leaves, stems, flowers, and/or fruits. Each type of disease or pest condition often presents a distinctive pattern, which can serve as a reference for diagnosing specific anomalies [4]. Traditionally, the identification of plant diseases has been conducted through direct visual inspection with the naked eye. This method relies on expert knowledge, requires considerable time, is subjective, and is prone to human error, leading to inaccurate identification results [5], [6]. Automatic identification has been developed by utilizing image processing methods and artificial intelligence. Image processing has been widely used in various fields such as health, agriculture, and so on. Image processing serves to improve the quality of visual representations used for the extraction of important information. In plant disease identification, leaf images can be used to detect pathological conditions using appropriate, efficient, and reliable image processing methodologies. The procedures covered in image processing techniques consist of several stages-image acquisition, image pre-processing, image segmentation, feature extraction, and classification [5-7]. Image acquisition is a method to acquire and capture high-quality images or photographs from various sources [7]. Images are produced with a variety of sensors, including cameras that capture visible light, infrared imaging technology, and other devices that operate in different electromagnetic wave ranges. These types of devices include digital cameras, thermal cameras, and hyperspectral cameras [4], [8], [9]. Preprocessing is a stage to prepare data according to the standard specifications needed for the next process. Preprocessing is done on the acquired image to improve image quality. Some of the preprocessing stages carried out include resizing, noise removal, color space conversion, smoothing, enhancement, and image restoration [4], [7], [10]. Image segmentation is the process of dividing an image into several discrete segments or areas. It aims to facilitate the identification of objects or features contained in the image [7], [10]. In plant disease identification, segmentation is done in two stages. In the first stage, leaves, fruits, or flowers are isolated from the background. In the second stage, healthy tissue is isolated from diseased tissue. Some of the segmentation methods used include k-means clustering, fuzzy C-Means (FCM), threshold-based methods. k-means is a clustering algorithm that groups data based on the similarity of feature values [11]. FCM is a clustering-based segmentation algorithm that allows each pixel to have a degree of membership in more than one cluster [12]. Otsu thresholding is a threshold-based segmentation method by determining a threshold value to separate objects from the background based on pixel intensity [13]. Feature extraction is the process of filtering important information from segmented images that will be used in the classification process [4]. The extracted features are color, shape, and texture. The main purpose of image classification is to identify and classify objects or patterns in the image [10]. The classification stage uses Artificial Intelligence, namely Machine Learning (ML) and Deep

Learning (DL) [14], [15]. DL is not only applied to the classification process, but also plays a role in the pre-processing, segmentation, feature extraction, and classification stages. Convolutional Neural Network (CNN) is a DL architecture that can be applied comprehensively in image processing systems [16-24].

This study provides a comprehensive overview of image-based plant disease identification for agriculture. The stages in plant disease identification include: image acquisition, image processing (pre-processing, segmentation, feature extraction), and image grouping using ML dan DL. This review supports continued progress in this field by providing valuable insights for researchers developing image-based methods for plant disease identification.

2. Methods

The literature review on image-based plant disease identification was conducted systematically and measurably. Systematic Literature Review (SLR) is a scientific research method that is conducted systematically, comprehensively, and objectively. It is used to identify, evaluate, and interpret all research related to a particular topic, research question, or phenomenon of interest [25], [26] as shown in Figure 1. The planning phase defines the goals of the systematic literature review, focusing on locating and evaluating relevant sources related to image-based plant disease identification. The conducting phase outlines how studies are chosen using specific inclusion and exclusion criteria, search strategies, and methods for data extraction and synthesis. Finally, the reporting phase involves sharing the findings.

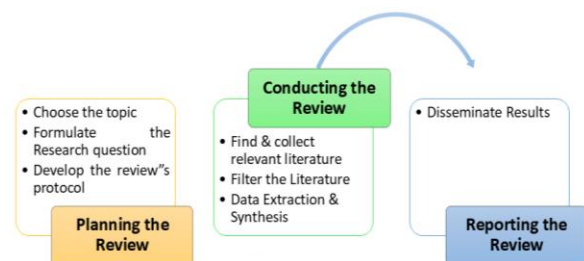


Figure 1. The Systematic Literature Review (SLR) Stages

The SLR method has been widely used to review research fields such as computer networks, education, medicine, and others [27], [28]. A comprehensive search for relevant information was conducted using digital databases. This systematic review utilizes the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) method [29], [30].

This review begins by formulating research questions based on the PICOC (Population, Intervention, Comparison, Outcome, Context) framework. The Population (P) focuses on plant diseases and image processing. The Intervention (I) involves aspects to be observed, specifically data acquisition techniques, image processing methods, and plant disease

classification methods. Comparison (C) is not defined in this review. The Outcome (O) of this study is the accuracy of the plant disease identification model. In this study, the context referred to includes publications in engineering, computer science, and agriculture journals.

Therefore, the Research Questions (RQs) are structured as follows:

RQ1: What datasets are used to identify plant diseases?

RQ2: What image processing techniques are applied to identify plant diseases?

RQ3: How is the performance of the classification methods used for plant disease identification?

RQ4: What are the challenges and limitations in applying image processing techniques for plant disease identification?

RQ5: What are the potential research areas in developing and improving plant disease identification models?

2.1 Data Source and Search Strategy

A literature search was conducted on July 31, 2025, using the Scopus database. Scopus is an internationally recognized abstract and citation database that indexes scholarly publications from a wide range of leading publishers. Therefore, the articles analyzed were drawn from journals and conference proceedings indexed in Scopus, including those published by IEEE, Elsevier, Springer, MDPI, and ACM. The search strategy employed keywords such as classification, image processing, plant diseases, machine learning, deep learning, and artificial intelligence, combined with Boolean operators (AND and OR).

The search was limited to publications from 2019 to 2025. Subject areas were Computer Science, Engineering, Agricultural and Biological Sciences, and Decision Sciences. Document types included articles and conference papers. Source types included journals and proceedings. Papers were written in English. All search results were exported in CSV format with complete metadata including author, title, year, source title, volume, issue, pages, DOI, affiliation, abstract, author keywords, index keywords, document type, and links. The complete search query structure applied to the information sources is presented in Table 1.

Table 1. Search Strategy

Database	Query
Scopus	(TITLE-ABS-KEY ("classification" AND "image processing" AND "plant disease" AND ("machine learning" OR "deep learning" OR "artificial intelligence"))) AND PUBYEAR > 2018 AND PUBYEAR < 2026 AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "AGRI") OR LIMIT-TO (SUBJAREA , "DECI")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")).

2.2 Eligibility Criteria

To select articles during the full-text review stage, eligibility criteria based on the research question were set to exclude irrelevant studies. These criteria are listed in Table 2.

Table 2. Eligibility Criteria

Description	Inclusion	Exclusion	Relation to RQ
The publication focuses on image-based detection, classification, and identification of plant diseases	√		All RQs
Articles published between 2019 and 2026	√		RQ4, RQ5
Publication is a research article	√		RQ1, RQ2, RQ3
articles written in English	√		All RQs
The publication topic is not relevant to image-based plant disease identification.		√	All RQs
Full Text Article is not Available		√	All RQs
Publications is a reviews or surveys papers		√	All RQs
The article is inaccessible		√	All RQs

2.3. Quality Assessment

Methodological quality assessment was assessed on studies meeting the inclusion criteria. The assessment criteria consisted of five questions, as shown in Table 3, designed to evaluate the overall quality of the studies.

Tabel 3. Quality Assessment Criteria

No.	Assesment Criteria	Score		
		Yes	Partially	No
1	Is the research objective formulated explicitly?	1	0	-1
2	Is the proposed methodology described in detail and systematically?	1	0	-1
3	Does the developed model demonstrate reliable performance based on appropriate evaluation metrics?	1	0	-1
4	Are the study's limitations explicitly described and adequately documented?	1	0	-1
5	Do the research results contribute directly and explicitly to answering the research questions?	1	0	-1

Based on the responses to these questions, each study received a cumulative score. Scores were assigned categorically: 1 (yes), 0 (partial), or -1 (no). Studies with a total score below 2 were deemed not to meet the quality threshold and were subsequently excluded from this review. Two reviewers independently assessed the studies, with a third reviewer consulted to resolve any disagreements.

2.4 Selection Process

After retrieving articles from the Scopus database, the initial step was to remove duplicate articles using the OpenRefine tool. The subsequent study selection process was carried out independently by two reviewers. In the first stage, title and abstract screening, the two reviewers independently assessed the initial suitability of each article based on the identification criteria. Articles were excluded if both reviewers agreed that the study was irrelevant. Articles deemed relevant or questionable by at least one reviewer proceeded to the next stage.

Articles that passed the title and abstract screening stage then proceeded to the eligibility assessment stage through full-text review. At this stage, the two reviewers independently read and evaluated the entire article content based on the eligibility criteria listed in Table 2. Any differences in assessment were recorded and discussed to reach a consensus. If no agreement was reached, a third reviewer was involved to make the final decision.

After articles were deemed to meet the eligibility criteria during the full-text review stage, a quality assessment was performed using the indicators listed in Table 3. Articles with a total score below the predetermined quality threshold were excluded from the review. If there was a disagreement between the two reviewers, a third reviewer was involved to resolve the issue.

The entire study selection process for this review was conducted systematically, as illustrated in Figure 2. The initial search of the selected databases identified 9,286 articles. Following the removal of 9,105 duplicates, 181 unique studies remained. After applying the selection and eligibility criteria, 82 studies were retained for the synthesis stage.

2.5 Data Extraction and Synthesis

Data were extracted from primary studies using a data extraction form, as shown in Table 4 designed to

systematically document all information relevant to the research questions. In multi-method studies, each different classification architecture was calculated separately; each study was calculated once for dataset characteristics; only the best results were recorded for performance metrics; and all preprocessing, segmentation, and feature extraction techniques were recorded in full. Percentages were rounded to two decimal places, and ambiguous cases were discussed until consensus was reached.

The distribution of selected studies by year is shown in Figure 3. From 2019 to June 2025, the number of studies on this topic increased, with 10 studies appearing by June 2025.

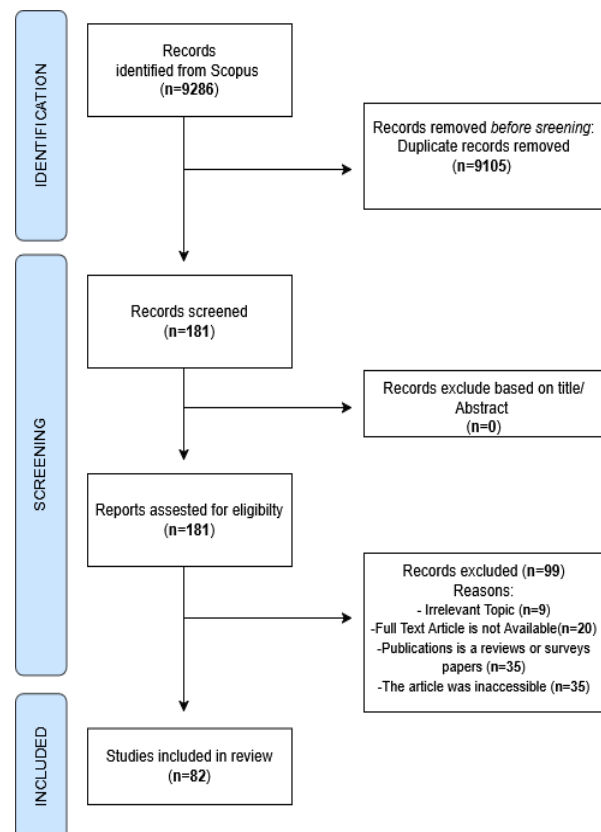


Figure 2. PRISMA Flow Diagram

Table 4. Data Extraction Form

No.	Variable	Description	RQ
1	Metadata	Metadata of paper (title, type of publication, publisher, year)	Study Overview
2	Dataset	source, accessibility, size	RQ1
3	Preprocessing Technique	image preprocessing techniques adopted in studies	RQ2
4	Segmentation Technique	Segmentation technique adopted in studies	RQ2
5	Feature Extraction Technique	Feature extraction method used in studies	RQ2
6	Classification Architecture	The classification architecture is divided M and DL	RQ3
7	Performance of Classification	performance metrics reported in plant disease identification studies	RQ3
8	Challenges and Limitations	inventory the obstacles identified in the application of image processing techniques for plant disease identification	RQ4
9	Future Works	This variable identifies the recommendations and research agenda proposed by the author to address the identified limitations.	RQ5

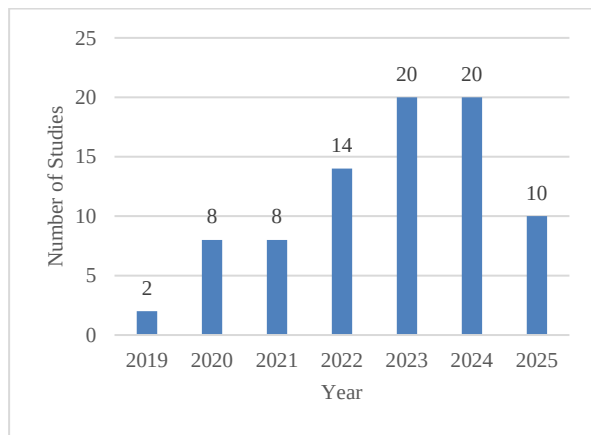


Figure 3. Distribution of Studies by Year

3. Results and Discussions

3.1 Source of Datasets

Plant disease identification models use various dataset sources to identify diseases accurately. Figure 4 shows the dataset sources used in the reviewed studies, namely PlantVillage, Plant Doc, EPPO Global Database, New Plant Disease, The International Rice Research Institute (IRRI), university fields, and laboratories.

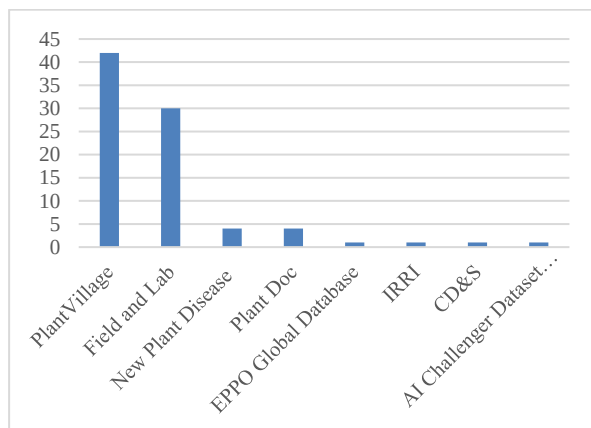


Figure 4. Distribution of dataset sources in reviewed studies

PlantVillage is the most widely used dataset [31-46], with 42 studies (51.22% of the total 82) utilizing this dataset. The PlantVillage dataset contains 54,309 images of healthy and diseased plants, representing 14 plant species, 38 plant disease classes, and one background class [47]. This dataset is a large, validated resource needed to build a reliable image classifier system [48]. The New Plant Disease dataset and PlantDoc were used 4 studies each (4.87% of the total studies). The New Plant Disease contains 87,000 RGB images of healthy and diseased plant leaves categorized into 38 different classes [49-51]. Plant Doc is a dataset for plant disease detection that includes 2,598 images for 13 plant species and 17 disease classes [52]. Another 4% of the studies obtained their image data from other online sources, namely Plant Doc [36], the EPPO Global Database [53], the International Rice Research Institute (IRRI) [54], CD&S dataset and AI Challenger Dataset 2018 [55]. The EPPO Global Database is

managed by the Secretariat of the European and Mediterranean Plant Protection Organization (EPPO) and contains pest-specific information for 97,800 agricultural, forestry, and plant protection entries [56]. The International Rice Research Institute (IRRI) is an agricultural research organization focused on rice [54].

While images obtained from online sources can offer a quick solution for researchers with limited access to plants, these datasets frequently include unwanted noise due to various factors such as climate, location, image size, and sensor quality. Consequently, researchers often gather data from specific field locations using diverse platforms [57-63]. Out of the reviewed studies, 30, or 36%, utilized datasets from university laboratories and field settings to capture images from real environments using digital cameras [64-69], mobile phone cameras [70-72], RGB cameras [11], VGA cameras [73], UAV cameras [74], and thermal cameras [75].

The use of various imaging devices faces the challenge of variability in the resulting leaf images, which is caused by environmental factors such as lighting, background, and weather. This variability significantly affects the color, texture, and overall quality of the captured images.

3.2 Image Processing Techniques

For further processing, image data is preprocessed using several different methods. This section discusses the various preprocessing, segmentation, and feature extraction methods that have been employed by the researchers in the studies.

The captured images will first be processed using various techniques. In this section, we will discuss some preprocessing techniques that various researchers have applied in their studies. Various studies have implemented pre-processing techniques to improve image quality before analysis. Common processes used include resizing, denoising, histogram equalization, and color conversion from RGB to grayscale or HSV [13], [20], [76-81]. Some studies also add a data augmentation stage with transformations such as rotation, translation, zoom, and contrast enhancement to expand the variety of training data [13], [77], [82-86]. In addition, median and Wiener filters are widely used for noise reduction and image smoothing [12], [13], [77], [87]. Other studies utilize advanced approaches, such as the Generative Adversarial Network (GAN)-based GauGAN algorithm to generate realistic synthetic images [18] and the NestNet technique for background removal [88]. Image enhancement efforts are also carried out using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method and affine transformation to improve contrast and visual structure [12], [83]. Overall, the combination of these techniques aims to produce cleaner, more uniform, and more representative images for subsequent segmentation and classification processes. Figure 5 shows the distribution of preprocessing methods used in this review.

For further evaluation, the techniques shown in Figure 5 are grouped into four categories: resizing, color conversion, image enhancement, and augmentation. Resizing includes both resizing and scaling. Image enhancement consists of histogram equalization, filtering (Gaussian, Median, Wiener), Fuzzy logic, NestNet, Quantum Fourier Processing, and contrast stretching. Color conversion includes RGB to Grayscale, RGB to HSV, RGB to HSI, and RGB to Lab. Augmentation consists of cropping, rotation, flipping, clipping, mirroring, shearing, inversion, and Generative Adversarial Networks (GAN).

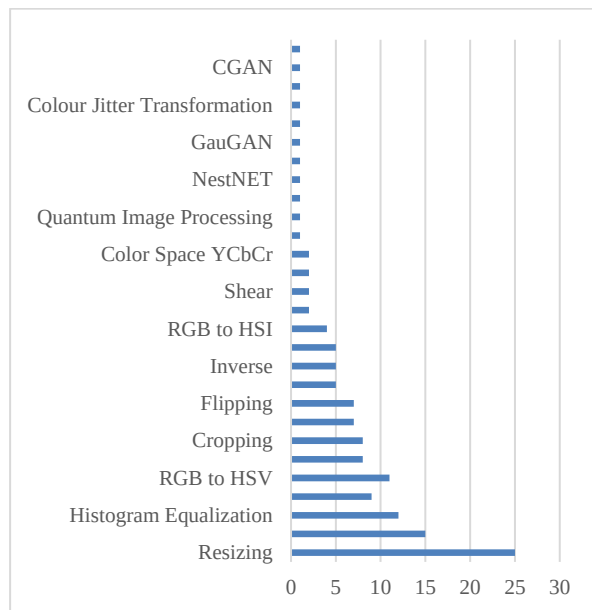


Figure 5. Preprocessing techniques in the studies reviewed

Figure 6 shows the distribution of preprocessing methods used. Of the studies examined, 18% utilized resizing, while 31% employed image enhancement. Color conversion was used in 21% of the studies, and data augmentation was applied in 30%.

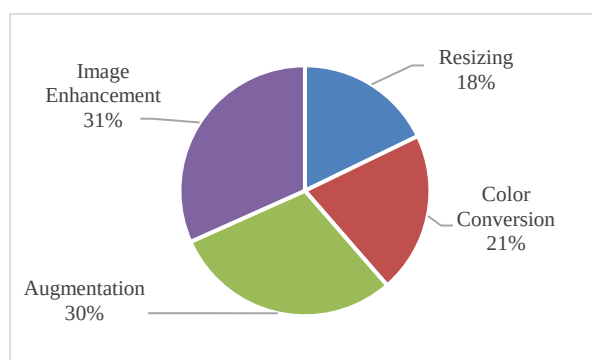


Figure 6. Distribution of preprocessing methods in review studies

In this segmentation section, we will explore several segmentation techniques that different researchers have utilized in their studies. Several studies have proposed various segmentation techniques to separate infected areas of plant leaves. The k-means clustering algorithm is widely used to segment images based on color or feature similarities [11]-[12], [20], [54], [67]-[68], [89]-[91]. This method works effectively when the

clusters have a hyperspherical distribution. Some studies combine k-means clustering with Lab* or HSV color space to improve segmentation accuracy [12], [53], [54], while others compare it with Canny edge detection and k-nearest neighbors, finding that k-means provides better predictions [90]. In addition, threshold-based methods such as Otsu and Kapur multi-level thresholding are also applied for background removal and object separation [13], [16], [88], [92-94]. The Fuzzy C-Means (FCM) algorithm that considers spatial information is used to strengthen the segmentation process [12], while a hybrid approach that combines Convolutional Neural Network (CNN) and Whale Optimization Algorithm (WOA) is developed to optimize the quality of segmentation results [22].

Among the studies reviewed, 46% utilized the k-means clustering technique, whereas 26% applied the Otsu method. Additionally, 9% of the studies implemented Fuzzy C-Means (FCM), and 16% employed alternative methods, including genetic algorithms, Kapur multi-level thresholding, HSV color space, and HCNWO. Figure 7 illustrates the overall application of different segmentation methods in the studies reviewed.

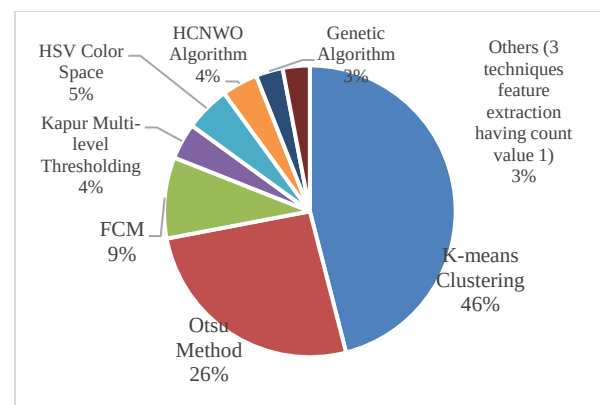


Figure 7. Distribution of segmentation methods in reviewed studies

This feature extraction section discusses various feature extraction techniques employed by researchers in their work. Some studies apply one or more techniques simultaneously to extract features.

Several studies have applied various feature extraction techniques to capture visual characteristics in plant leaf images. The Gray Level Co-occurrence Matrix (GLCM) method is widely used to extract texture features, such as contrast, correlation, entropy, energy, and homogeneity [13], [54], [59], [67], [76], [90], [95-97]. Some studies combine GLCM with color or shape descriptors to improve discriminative ability [13], [53], [71], [95], [98]. Another approach uses Local Binary Pattern (LBP) to describe texture [11], [49], [66], [99], which is often combined with Principal Component Analysis (PCA) to reduce feature dimensionality [66]. In addition, gradient and invariant-based descriptors such as Histogram of Oriented Gradients (HOG) [51] and Scale Invariant Feature Transform (SIFT) combined with Entropy-ELM and Whale Optimization Algorithm (WOA) are also used for optimal feature

selection [100]. On the other hand, Convolutional Neural Network (CNN) is increasingly used to perform automatic and hierarchical feature extraction [18], [31], [33], [38], [77], [75], [101].

Figure 8 illustrates the distribution of various feature extraction methods used in the reviewed studies. Of the studies examined, 25% employed CNN, followed by 12% using GLCM. Combining color and texture features for feature extraction was found in 3% of the studies, whereas the combination of color, texture, and shape features appeared in 8% of the studies. MobileNetV3 used by 4%, while both LBP and DCNN were used in 3% of the cases each. Each of the remaining 29 techniques was employed individually in just 1% of the cases.

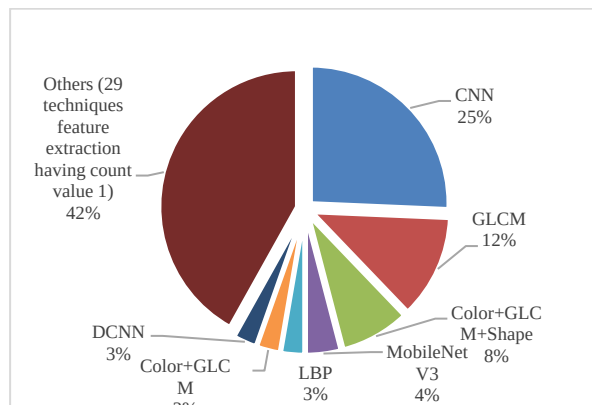


Figure 8. Distribution of feature extraction techniques in this review

3.3 Performance of Classification Method

The evaluated studies employed various approaches to classify plant diseases, specifically ML and DL techniques.

In the ML, the Support Vector Machine (SVM) method is widely used with high accuracy, such as in the study [46] which classified tomato leaves into 10 classes with an accuracy of 90.37%, and several other studies reported accuracy above 97% [11], [73], [69], [82], [84], [95]. SVM is also used to detect diseases in various plants, such as rice [38], [89], corn [90], grapes [21], and dates [95]. The combination of Principal Component Analysis (PCA) and Gray Level Co-occurrence Matrix (GLCM) with SVM produces accuracy up to 98.97% [21]. In addition, the Random Forest (RF) method shows competitive performance with accuracy reaching 96.17% on potato leaves [71] and more than 97% on apple leaves [72]. Other approaches, such as the Bagged Tree Classifier, even achieved 100% accuracy in fruit fly disease classification [66]. In the DL category, CNN showed excellent results, with accuracy reaching 99.62% on tomato plants [37]. Architectures such as MobileNet [18], AlexNet, VGG16/19 [24], InceptionV3, and DenseNet [50] also produced high accuracy ranging from 91% to 99%, depending on the type of plant and the augmentation data used.

Based on the examined studies, the performance accuracy of the classification methods was categorized into three groups: <80%, 80%–<90%, and ≥90%. Figure 9 presents the accuracy distribution across 66 studies, revealing that 92% achieved a plant disease identification accuracy of over 90%, 4.54% attained an accuracy between 80% and 90%, and 3.03% achieved an accuracy below 80%.

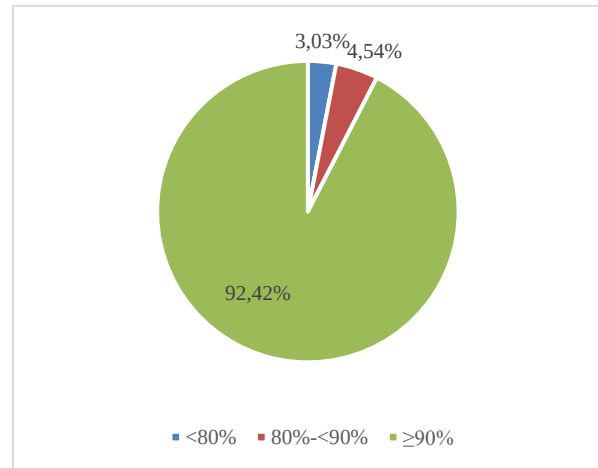


Figure 9. Accuracy of Classification Methods in this review

3.4 The Challenges and Limitations

According to the analyzed studies, several challenges and limitations encountered in the identification of plant diseases through image analysis include:

The PlantVillage dataset is the most widely used in image-based plant disease identification studies. While this dataset has the advantage of being a large, structured, public dataset covering a wide range of plant diseases, its controlled image capture with uniform backgrounds, stable lighting, and high resolution often results in trained models being less robust to real-world variations such as shadows, complex backgrounds, or changing weather conditions [32], [42], [81]. As a result, although many studies claim accuracy of over 90%, the performance of such models often drops sharply when tested in real environments [34]. Additionally, the PlantVillage dataset shows an unbalanced distribution of data between classes, where some classes of plant diseases or conditions have a significantly larger number of images compared to other classes [42], [81]. This imbalance causes ML and DL models to be biased towards the majority class, meaning the model often predicts the class that appears most frequently in the training data, resulting in a model with a seemingly high accuracy, but failing to recognize and learn patterns from the minority class well [5], [33].

K-means clustering remains the most used for leaf segmentation in plant disease detection systems. The reason for this is k-means has the advantages of being simple, computationally light, and easy to implement, especially in studies that utilize images taken with a uniform background and constant lighting. Therefore, k-means is quite efficient in separating leaf parts from the background by considering color differences in

RGB, HSV, or Lab color spaces [4], [102]. However, this algorithm is less than optimal for images with diverse backgrounds and lighting. In addition, this algorithm cannot automatically initiate cluster centers [20]. This condition often results in inaccurate segmentation results, thus impacting the accuracy in extracting important features from the image and ultimately reducing accuracy during the classification process.

CNNs are widely used in DL-based image processing, primarily due to their ability to perform two tasks simultaneously: extracting important features and classifying them [31], [77], [93]. With the ability to learn directly from raw images, CNNs can automatically detect disease characteristics such as spot shape, pigment changes, or abnormal texture patterns on leaves. CNNs are very reliable in detecting plant diseases when images are taken in a controlled environment, for example with a plain background, consistent lighting, and a fixed camera position [48]. However, implementing CNNs requires the availability of large and accurately labeled training data, which is often limited for rare diseases or local plant species with minimal documentation. In addition, CNNs are quite sensitive to changes in the surrounding environment, such as changing light, busy backgrounds, or inconsistent shooting angles. This can affect accuracy when applied to field data. In addition, CNN working processes are often less transparent, making it difficult to explain the basis of classification results. On the other hand, CNN architectures involve millions of parameters and repeated convolution operations applied to thousands of leaf images of various sizes and resolutions, thus requiring high computational resources. This is a challenge in applying CNN directly to agricultural equipment in the field.

3.5 The Potential Research Areas in Plant Disease Identification

Developing and improving plant disease identification models necessitates collaboration among agricultural science, technology, and data science. Here are some potential research opportunities in this field:

To overcome dataset limitations is to compile a broader, more diverse, and well-labeled dataset, and utilize data augmentation techniques to increase the variety and quality of training data.

The application of artificial intelligence models in the agricultural context also requires consideration of ethical and data privacy aspects. The process of acquiring and processing plant images often involves information originating from agricultural land owned by individuals or groups, which may contain sensitive information, such as geographic location or the identity of landowners. Therefore, data collection and utilization need to be carried out with clear permissions, secure storage, and limited use for research purposes or improving agricultural services. Therefore, future research should emphasize the importance of

transparency and data security policies to maintain user trust in AI-based systems.

Development of image processing techniques to achieve better segmentation and feature extraction results to produce accurate identification. Integrating multiple segmentation methods to leverage the strengths of each approach. This hybrid approach can produce better accuracy and adaptability in image segmentation. Improved feature extraction by combining several feature extraction techniques. These techniques can help capture subtle patterns associated with various diseases.

Developing more comprehensive model evaluation standards should be a focus of future research. In addition to accuracy, metrics such as precision, recall, F1 score, and confusion matrix should be reported to provide a more complete picture and avoid misdiagnosis in real-world applications. Accuracy indicates the proportion of correct predictions, but is less representative when the data is imbalanced. Precision assesses the accuracy of positive predictions, recall measures the model's ability to detect all positive cases, while the F1 score balances the two using the harmonic mean. Confusion matrix analysis is used to assess the distribution of correct and incorrect predictions for each disease class, including True Positive, True Negative, False Positive, and False Negative values. This combination of metrics provides a more comprehensive evaluation of the model's strengths and weaknesses in accurately identifying plant diseases.

For practical implementation in the field, future research should focus on developing DL models integrated into lightweight mobile applications tailored to farmers' needs. Model architecture needs to be optimized for direct execution on resource-constrained devices. Furthermore, a simple, mobile-compatible user interface is required. Explained AI (XAI) is applied to interpret the decisions of deep learning models, enabling farmers to understand the rationale behind diagnoses and building trust in the system. Furthermore, these models are integrated into a Decision Support System (DSS) capable of translating prediction results into relevant and contextual action recommendations. Therefore, future research should not only focus on improving algorithm performance but also consider usability and user trust. This way, DL-based solutions can be truly utilized by farmers in the field in a practical and effective manner.

4. Conclusions

In this article, a comprehensive review of plant disease identification using image processing techniques is presented, based on 82 studies resulting from a systematic review conducted using the PRISMA method. Five research questions guided this review, focusing on various aspects such as the datasets used for plant disease identification, image processing methods,

and the accuracy of classification methods, including both ML and DL approaches.

The review shows that most studies rely on the PlantVillage dataset, which is supplemented with images from digital cameras and mobile phones. Preprocessing generally involves enhancement and augmentation; k-means dominates segmentation, and CNNs are the primary method for feature extraction. Notably, 61 studies reported accuracy above 90%. The main challenges fall into three dimensions: data, methodology, and practice. Data are often controlled and imbalanced, limiting generalizability in real-world settings. Methodologically, classical segmentation is sensitive to environmental variability, while deep learning models require substantial computational resources and are susceptible to distributional shifts. Practically, deployment on mobile devices and the need for interpretability through XAI remain key concerns.

Future work should emphasize more representative datasets, hybrid approaches of classical and deep learning, and lightweight and adaptive decision support systems for real-world agricultural environments.

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References

- [1] *The Global Action for Fall Armyworm Control: A resource mobilization guide*. FAO, 2022. doi: <https://doi.org/10.4060/cb8910en>
- [2] "The Challenge." Accessed: Apr. 23, 2025. [Online]. Available: <https://www.fao.org/4/k6021e/k6021e.pdf>
- [3] R. Acharya et al., "Climate change impact on soil health and crop production," *International Journal of Research in Agronomy*, vol. 7, no. 4, pp. 150–156, Apr. 2024, doi: <https://doi.org/10.33545/2618060X.2024.v7.i4c.540>
- [4] L. C. Ngugi, M. Abelwahab, and M. Abo-Zahhad, "Recent advances in image processing techniques for automated leaf pest and disease recognition – A review," Mar. 01, 2021, *China Agricultural University*. doi: <https://doi.org/10.1016/j.inpa.2020.04.004>
- [5] A. Tabbakh and S. S. Barpanda, "Evaluation of Machine Learning Models for Plant Disease Classification Using Modified GLCM and Wavelet Based Statistical Features," *Traitement du Signal*, vol. 39, no. 6, pp. 1893–1905, Dec. 2022, doi: <https://doi.org/10.18280/ts.390602>
- [6] M. Ilsever and I. Baz, "Consistency regularization based semi-supervised plant disease recognition," *Smart Agricultural Technology*, vol. 9, Dec. 2024, doi: <https://doi.org/10.1016/j.atech.2024.100613>
- [7] M. Singh, S. Ayuub, A. Baronia, and D. Soni, "Analysis and Implementation of Disease Detection in Leafs and Fruit Using Image Processing and Machine Learning," *SN Comput. Sci.*, vol. 4, no. 5, Sep. 2023. doi: <https://doi.org/10.1007/s42979-023-02045-z>
- [8] A. Ahmad, D. Saraswat, and A. El Gamal, "A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools," Feb. 01, 2023, *Elsevier B.V.* doi: <https://doi.org/10.1016/j.atech.2022.100083>
- [9] A. Das, F. Pathan, J. R. Jim, M. M. Kabir, and M. F. Mridha, "Deep learning-based classification, detection, and segmentation of tomato leaf diseases: A state-of-the-art review," Jun. 01, 2025, *KeAi Communications Co.* doi: <https://doi.org/10.1016/j.aiaa.2025.02.006>
- [10] H. Ulutas and V. Aslantas, "A Fast and Accurate Method for Classifying Tomato Plant Health Status Using Machine Learning and Image Processing," *Elektronika ir Elektrotechnika*, vol. 29, no. 2, pp. 54–68, 2023, doi: <https://doi.org/10.5755/j02.eie.33866>
- [11] M. Jamjoom, A. Elhadad, H. Abulkasim, and S. Abbas, "Plant Leaf Diseases Classification Using Improved K-Means Clustering and SVM Algorithm for Segmentation," *Computers, Materials and Continua*, vol. 76, no. 1, pp. 367–382, 2023, doi: <https://doi.org/10.32604/cmc.2023.037310>
- [12] S. Alzoubi, M. Jawameh, Q. Bsoul, I. Keshta, M. Soni, and M. A. Khan, "An advanced approach for fig leaf disease detection and classification: Leveraging image processing and enhanced support vector machine methodology," *Open Life Sci.*, vol. 18, no. 1, Jan. 2023, doi: <https://doi.org/10.1515/biol-2022-0764>
- [13] S. Poornima, N. Sripriya, A. F. Alrashedi, S. S. Askar, and M. Abouhawwash, "Hybrid Convolutional Neural Network for Plant Diseases Prediction," *Intelligent Automation and Soft Computing*, vol. 36, no. 2, pp. 2393–2409, 2023, doi: <https://doi.org/10.32604/iasc.2023.024820>
- [14] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 305–310, Jun. 2022, doi: <https://doi.org/10.1016/j.gltp.2022.03.016>
- [15] N. Nigar, H. Muhammad Faisal, M. Umer, O. Oki, and J. Manappattukunnel Lukose, "Improving Plant Disease Classification with Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence," *IEEE Access*, vol. 12, pp. 100005–100014, 2024, doi: <https://doi.org/10.1109/ACCESS.2024.3428553>
- [16] P. K. Srivastava, D. K. Ghosh, A. Arora, and P. Johri, "Advanced Computer Vision Framework Using Convolutional Neural Network for Plant Leaf Disease Identification," 2024, doi: <https://nano-ntp.com/index.php/nano/article/view/827>
- [17] E. Moupojou, F. Retraint, H. Tapamo, M. Nkenlifack, C. Kacfeh, and A. Tagne, "Segment Anything Model and Fully Convolutional Data Description for Plant Multi-Disease Detection on Field Images," *IEEE Access*, vol. 12, pp. 102592–102605, 2024, doi: <https://doi.org/10.1109/ACCESS.2024.3433495>
- [18] S. B. Cho, Y. Cheng, and S. Sul, "Enhanced classification performance through GauGAN-based data augmentation for tomato leaf images," *IET Image Process.*, 2024, doi: <https://doi.org/10.1049/ipr2.13069>
- [19] P. Jha, D. Dembla, and W. Dubey, "Implementation of transfer learning based ensemble model using image processing for detection of potato and bell pepper leaf diseases," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 8s, pp. 69–80, 2024, doi: <https://www.ijisae.org/index.php/IJISAE/article/view/4097>
- [20] B. Igried, S. AlZu'bi, D. Aqel, A. Mughaid, I. Ghaith, and L. Abualigah, "An Intelligent and Precise Agriculture Model in Sustainable Cities Based on Visualized Symptoms," *Agriculture (Switzerland)*, vol. 13, no. 4, Apr. 2023, doi: <https://doi.org/10.3390/agriculture13040889>
- [21] S. M. Javidan, A. Banakar, K. A. Vakilian, and Y. Ampatzidis, "Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning," *Smart Agricultural Technology*, vol. 3, Feb. 2023, doi: <https://doi.org/10.1016/j.atech.2022.100081>
- [22] E. Banu and A. Geetha, "Hybrid convolutional neural network with whale optimization algorithm (Hcnwno) based plant leaf diseases detection," *Data and Metadata*, vol. 2, 2023, doi: <https://doi.org/10.56294/dm2023196>
- [23] S. Quan, J. Wang, Z. Jia, M. Yang, and Q. Xu, "MS-Net: a novel lightweight and precise model for plant disease identification," *Front. Plant Sci.*, vol. 14, 2023, doi: <https://doi.org/10.3389/fpls.2023.1276728>
- [24] A. Elaraby, W. Hamdy, and S. Alanazi, "Classification of Citrus Diseases Using Optimization Deep Learning Approach," *Comput. Intell. Neurosci.*, vol. 2022, no. 1, p. 9153207, 2022, doi: <https://doi.org/10.1155/2022/9153207>

- [25] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," 2007. <https://docs.edtechhub.org/lib/EDAG684W>
- [26] P. A. Quezada-Sarmiento, J. A. Elorriaga, A. Arruarte, and H. Washizaki, "Open BOK on software engineering educational context: A systematic literature review," Sep. 01, 2020, MDPI. doi: <https://doi.org/10.3390/su12176858>
- [27] M. Ilhamdi Rusydi, R. Kurnia, B. Sunaryo, and A. Ramadhani, "A Systematic Review of Noninvasive Blood Glucose Estimation Using Near Infrared," *International Journal of Intelligent Systems and Applications in Engineering IJISAE*, vol. 12, no. 4, pp. 59–76, Jun. 2024, [Online]. Available: <https://ijisae.org/index.php/IJISAE/article/view/6174>
- [28] B. Sunaryo, M. I. Rusydi, A. Hazmi, and M. Sasaki, "A Systematic Literature Review of Automation Quality of Service in Computer Networks: Research Trends, Datasets, and Methods," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 7, no. 2, pp. 353–366, Mar. 2023, doi: <https://doi.org/10.29207/resti.v7i2.4810>
- [29] M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," Mar. 29, 2021, *BMJ Publishing Group*. doi: <https://doi.org/10.1136/bmj.n71>
- [30] M. J. Page et al., "PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews," Mar. 29, 2021, *BMJ Publishing Group*. doi: <https://doi.org/10.1136/bmj.n160>
- [31] R. Jain, S. K. Bekele, D. Palaniappan, K. Parmar, and T. Premavathi, "Employing Deep Convolutional Neural Networks for Enhanced Precision in Potato and Maize Leaf Disease Detection and Classification," *Turkish Journal of Engineering*, vol. 9, no. 2, pp. 290–301, Jun. 2025, doi: <https://doi.org/10.31127/tuje.1581124>
- [32] B. Ramana Reddy, G. Kalnoor, M. Devashish, and P. Sai Karthik Reddy, "Deep Learning Based Mobile Application for Automated Plant Disease Detection," *IEEE Access*, vol. 13, pp. 107917–107925, 2025, doi: <https://doi.org/10.1109/ACCESS.2025.3581099>
- [33] W. C. Yong, K. W. Ng, S. C. Haw, P. Naveen, and S. B. Ng, "Leaf Condition Analysis Using Convolutional Neural Network and Vision Transformer," *International Journal of Computing and Digital Systems*, vol. 16, no. 1, pp. 1685–1695, Oct. 2024, doi: <http://dx.doi.org/10.12785/ijcds/1601125>
- [34] M. Rajagopal, S. Kayikci, M. Abbas, and R. Sivasakthivel, "A novel technique for leaf disease classification using Legion Kernels with parallel support vector machine (LK-PSVM) and fuzzy C means image segmentation," *Heliyon*, vol. 10, no. 12, p. e32707, 2024, doi: <https://doi.org/10.1016/j.heliyon.2024.e32707>
- [35] M. Rezaei, D. Diepeveen, H. Laga, M. G. K. Jones, and F. Sohel, "Plant disease recognition in a low data scenario using few-shot learning," *Comput. Electron. Agric.*, vol. 219, Apr. 2024, doi: <https://doi.org/10.1016/j.compag.2024.108812>
- [36] L. Liu et al., "A multi-scale feature fusion neural network for multi-class disease classification on the maize leaf images," *Heliyon*, vol. 10, no. 7, Apr. 2024, doi: <https://doi.org/10.1016/j.heliyon.2024.e28264>
- [37] D. MITRA, A. GOYAL, S. GUPTA, H. S. KANYAL, S. KAUSHIK, and K. KUMAR, "Automated tomato leaf disease detection technique using deep learning," *J. Theor. Appl. Inf. Technol.*, vol. 101, no. 14, 2023. Available: <https://jatit.org/volumes/Vol101No14/25Vol101No14.pdf>
- [38] A. K. Dixit and R. Verma, "Advanced Hybrid Model for Multi Paddy diseases detection using Deep Learning," *EAI Endorsed Trans. Pervasive Health Technol.*, vol. 9, no. 1, May 2023, doi: <https://doi.org/10.4108/eetpht.9.4481>
- [39] R. A. Mulla, M. E. Pawar, S. S. Banait, S. N. Ajani, M. P. Borawake, and S. Hundekari, "Design and Implementation of Deep Learning Method for Disease Identification in Plant Leaf," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, pp. 278–285, 2023, doi: <https://doi.org/10.17762/ijritcc.v11i2s.6147>
- [40] J. Zheng and M. Du, "Study on Tomato Disease Classification based on Leaf Image Recognition based on Deep Learning Technology," [Online]. doi: <https://doi.org/10.14569/IJACSA.2023.0140463>
- [41] A. Alpyssov et al., "ASSESSMENT OF PLANT DISEASE DETECTION BY DEEP LEARNING," *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 2–121, pp. 41–48, 2023, doi: <https://doi.org/10.15587/1729-4061.2023.274483>
- [42] A. O. Anim-Ayeko, C. Schillaci, and A. Lipani, "Automatic blight disease detection in potato (*Solanum tuberosum* L.) and tomato (*Solanum lycopersicum*, L. 1753) plants using deep learning," *Smart Agricultural Technology*, vol. 4, Aug. 2023, doi: <https://doi.org/10.1016/j.atech.2023.100178>
- [43] M. Yang and S. Ding, "Algorithm for appearance simulation of plant diseases based on symptom classification," *Front. Plant Sci.*, vol. 13, Jul. 2022, doi: <https://doi.org/10.3389/fpls.2022.935157>
- [44] K. Jayaprakash and S. P. Balamurugan, "Analysis of Plant Disease Detection and Classification Models: A Computer Vision Perspective," *J. Comput. Theor. Nanosci.*, vol. 17, no. 12, pp. 5422–5428, 2020, doi: <https://doi.org/10.1166/jctn.2020.9435>
- [45] R. M. J. Al-Akkam and M. S. M. Altaei, "Plants Leaf Diseases Detection Using Deep Learning," *Iraqi Journal of Science*, pp. 801–816, 2022, doi: <https://doi.org/10.24996/ijis.2022.63.2.34>
- [46] Wiharto, F. H. Nashrullah, E. Suryani, U. Salamah, N. P. T. Prakisy, and S. Setyawan, "Texture-based feature extraction using gabor filters to detect diseases of tomato leaves," *Revue d'Intelligence Artificielle*, vol. 35, no. 4, pp. 331–339, Aug. 2021, doi: <https://doi.org/10.18280/ria.350408>
- [47] D. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," *arXiv preprint arXiv:1511.08060*, 2015. doi: <https://doi.org/10.48550/arXiv.1511.08060>
- [48] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, p. 1419, 2016. doi: <https://doi.org/10.3389/fpls.2016.01419>
- [49] S. Alqethami, W. Alzhrani, B. Almtanni, and M. Alghamdi, "Disease Detection in Apple Leaves Using Image Processing Techniques," 2022. [Online]. doi: <https://doi.org/10.48084/etasr.4721>
- [50] R. M. Prakash, M. Vimala, K. Ramalakshmi, M. B. Prakash, A. Krishnamoorthi, and R. S. S. Kumari, "Crop Disease Detection and Classification with Transfer learning and hyper-parameters optimized Convolutional neural network," in *Proceedings of the 2022 3rd International Conference on Intelligent Computing, Instrumentation and Control Technologies: Computational Intelligence for Smart Systems, ICICICT 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 1608–1613. doi: <https://doi.org/10.1109/ICICICT54557.2022.9917901>
- [51] R. Cristin, B. S. Kumar, C. Priya, and K. Karthick, "Deep neural network based Rider-Cuckoo Search Algorithm for plant disease detection," *Artif. Intell. Rev.*, vol. 53, no. 7, pp. 4993–5018, Oct. 2020, doi: <https://doi.org/10.1007/s10462-020-09813-w>
- [52] D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, and N. Batra, "PlantDoc: A dataset for visual plant disease detection," in *Proceedings of the 7th ACM IKDD CoDS and 25th COMAD*, 2020, pp. 249–253. doi: <https://doi.org/10.1145/3371158.3371196>
- [53] M. Baljon, "A Framework for Agriculture Plant Disease Prediction using Deep Learning Classifier," 2023. [Online]. doi: <https://doi.org/10.14569/IJACSA.2023.01408119>
- [54] A. F. A. Ahmad Effendi, M. N. Md Isa, M. I. Ahmad, M. F. Che Husin, and S. Z. Md Naziri, "Image Processing for Paddy Disease Detection Using K-Means Clustering and GLCM Algorithm," 2021. Available: <https://ijneam.unimap.edu.my>
- [55] J. Lin et al., "Local and Global Feature-Aware Dual-Branch Networks for Plant Disease Recognition," *Plant Phenomics*, vol. 6, 2024, doi: <https://doi.org/10.34133/plantphenomics.0208>
- [56] M. C. Rosace et al., "A spatio-temporal dataset of plant pests' first introductions across the EU and potential entry pathways," *Sci. Data*, vol. 10, no. 1, p. 731, 2023. Doi: <https://doi.org/10.1038/s41597-023-02643-9>
- [57] D. T. Mukhamedieva and R. A. Sobirov, "Application of quantum computing in image processing for recognition of

- infectious diseases of wheat,” in *BIO Web of Conferences*, EDP Sciences, Mar. 2024. doi: <https://doi.org/10.1051/bioconf/20249501003>
- [58] S. M. Javidan, A. Banakar, K. A. Vakilian, Y. Ampatzidis, and K. Rahnama, “Early detection and spectral signature identification of tomato fungal diseases (*Alternaria alternata*, *Alternaria solani*, *Botrytis cinerea*, and *Fusarium oxysporum*) by RGB and hyperspectral image analysis and machine learning,” *Heliyon*, vol. 10, no. 19, p. e38017, 2024, doi: <https://doi.org/10.1016/j.heliyon.2024.e38017>
- [59] R. S. Jesie, M. S. Godwin Premi, and T. Jarin, “Comparative analysis of paddy leaf diseases sensing with a hybrid convolutional neural network model,” *Measurement: Sensors*, vol. 31, Feb. 2024, doi: <https://doi.org/10.1016/j.measen.2023.100966>
- [60] S. V. A. Bhagwat, and V. Laxmi, “LeafSpotNet: A deep learning framework for detecting leaf spot disease in jasmine plants,” *Artificial Intelligence in Agriculture*, vol. 12, pp. 1–18, Jun. 2024, doi: <https://doi.org/10.1016/j.aiia.2024.02.002>
- [61] O. N. R. Balaga and U. B. Patayon, “Effectiveness of Background Segmentation Algorithm and Deep Learning Technique for Detecting Anthracnose (leaf blight) and *Golovinomyces cichoracearum* (powdery mildew) in Rubber Plant,” in *Procedia Computer Science*, Elsevier B.V., 2024, pp. 294–301. doi: <https://doi.org/10.1016/j.procs.2024.03.013>
- [62] S. Terensan, A. S. A. Salgadoe, N. S. Kottearachchi, and O. V. D. S. Jagathpriya Weerasena, “Proximally sensed RGB images and colour indices for distinguishing rice blast and brown spot diseases by k-means clustering: Towards a mobile application solution,” *Smart Agricultural Technology*, vol. 9, Dec. 2024, doi: <https://doi.org/10.1016/j.atech.2024.100532>
- [63] S. I. Prottasha and S. M. S. Reza, “A classification model based on depthwise separable convolutional neural network to identify rice plant diseases,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 4, pp. 3642–3654, Aug. 2022, doi: <http://doi.org/10.11591/ijece.v12i4.pp3642-3654>
- [64] D. Kumar and V. Kukreja, “Combined CNN with STARGAN for Wheat Yellow Rust Disease Classification,” *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 1081–1095, 2023. Available: <https://hdl.handle.net/20.500.14536/4788>
- [65] A. Bhujel et al., “Detection of gray mold disease and its severity on strawberry using deep learning networks,” *Journal of Plant Diseases and Protection*, vol. 129, no. 3, pp. 579–592, Jun. 2022, doi: <https://doi.org/10.1007/s41348-022-00578-8>
- [66] O. Almutiry et al., “A Novel Framework for Multi-Classification of Guava Disease,” *Computers, Materials & Continua*, vol. 69, no. 2, pp. 1915–1926, 2021, doi: <https://doi.org/10.32604/cmc.2021.017702>
- [67] Anjna, M. Sood, and P. K. Singh, “Hybrid System for Detection and Classification of Plant Disease Using Qualitative Texture Features Analysis,” in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 1056–1065. doi: <https://doi.org/10.1016/j.procs.2020.03.404>
- [68] A. Sinha and R. S. Shekhawat, “Olive Spot Disease Detection and Classification using Analysis of Leaf Image Textures,” in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 2328–2336. doi: <https://doi.org/10.1016/j.procs.2020.03.285>
- [69] M. Türkoğlu and D. Hanbay, “Plant disease and pest detection using deep learning-based features,” *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 27, no. 3, pp. 1636–1651, 2019. doi: <https://doi.org/10.3906/elk-1809-181>
- [70] R. Guo et al., “CTDUNet: A Multimodal CNN–Transformer Dual U-Shaped Network with Coordinate Space Attention for *Camellia oleifera* Pests and Diseases Segmentation in Complex Environments,” *Plants*, vol. 13, no. 16, Aug. 2024, doi: <https://doi.org/10.3390/plants13162274>
- [71] H. K. Talab, D. Mohammadzamani, and M. G. Parashkoohi, “Investigating the accuracy of classification in unbalanced data in order to diagnose two common potato leaf diseases (early blight and late blight) using image processing and machine learning,” *Discover Applied Sciences*, vol. 6, no. 6, p. 286, May 2024, doi: <https://doi.org/10.1007/s42452-024-05959-2>
- [72] V. K. Vishnoi, K. Kumar, and B. Kumar, “Crop Disease Classification Through Image Processing and Machine Learning Techniques Using Leaf Images,” in *2021 First International Conference on Advances in Computing and Future Communication Technologies (ICACFCT)*, 2021, pp. 27–32. doi: <https://doi.org/10.1109/icacfct53978.2021.9837353>
- [73] M. G. Balram, A. P. Vaddeswaram, and K. Kiran Kumar, “Crop Field Monitoring and Disease Detection of Plants in Smart Agriculture using Internet of Things.” [Online]. doi: <http://dx.doi.org/10.14569/IJACSA.2022.0130795>
- [74] K. Demir and V. Tümen, “Drone-assisted automated plant diseases identification using spiking deep convolutional neural learning,” *AI Communications*, vol. 34, no. 2, pp. 147–162, Sep. 2021, doi: <https://doi.org/10.3233/AIC-210009>
- [75] G. Batchuluun, S. H. Nam, and K. R. Park, “Deep learning-based plant classification and crop disease classification by thermal camera,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 10474–10486, Nov. 2022, doi: <https://doi.org/10.1016/j.jksuci.2022.11.003>
- [76] A. Kumar, P. Kumar, and K. Suman, “Deep Learning for Automated Diagnosis of Plant Diseases: A Technological Approach,” 2024, doi: <https://doi.org/10.52783/jes.655>
- [77] P. Bansal, Ranvijay, and M. Yadav, “Automatic detection of plant leaf diseases using deep learning,” *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 901–910, 2023. Available: <https://hdl.handle.net/20.500.14536/4776>
- [78] M. Pavicic, K. Overmyer, A. ur Rehman, P. Jones, D. Jacobson, and K. Himanen, “Image-Based Methods to Score Fungal Pathogen Symptom Progression and Severity in Excised *Arabidopsis* Leaves,” *Plants*, vol. 10, no. 1, p. 158, Jan. 2021, doi: <https://doi.org/10.3390/plants10010158>
- [79] S. Madhu and V. Ravisanakar, “Comprehensive Analysis of a YOLO-based Deep Learning Model for Cotton Plant Leaf Disease Detection,” *Engineering, Technology and Applied Science Research*, vol. 15, no. 1, pp. 19947–19952, Feb. 2025, doi: <https://doi.org/10.48084/etasr.8944>
- [80] E. Siaga and S. Samsuryadi, “Hybrid DCNN-SVM Architecture for Optimizing Sugarcane Leaf Disease Classification,” 2025. [Online]. Available: <https://www.iaeng.org/IJCS/>
- [81] A. H. Ali, A. Youssef, M. Abdelal, and M. A. Raja, “An ensemble of deep learning architectures for accurate plant disease classification,” *Ecol. Inform.*, vol. 81, p. 102618, 2024, doi: <https://doi.org/10.1016/j.ecoinf.2024.102618>
- [82] R. M. Alyas and A. S. Mohammed, “Detection of Plant Diseases using Image Processing with Machine Learning,” in *2022 2nd International Conference on Computing and Machine Intelligence, ICMI 2022 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: <https://doi.org/10.1109/ICMI55296.2022.9873793>
- [83] K. Kusrini et al., “Data augmentation for automated pest classification in Mango farms,” *Comput. Electron. Agric.*, vol. 179, Dec. 2020, doi: <https://doi.org/10.1016/j.compag.2020.105842>
- [84] M. I. Pavel, S. M. Kamruzzaman, S. S. Hasan, and S. R. Sabuj, “An IoT Based Plant Health Monitoring System Implementing Image Processing,” in *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS)*, IEEE, Feb. 2019, pp. 299–303. doi: <https://doi.org/10.1109/CCOMS.2019.8821782>
- [85] M. A. Mahmood and K. Alsalem, “Olive Leaf Disease Detection via Wavelet Transform and Feature Fusion of Pre-Trained Deep Learning Models,” *Computers, Materials and Continua*, vol. 78, no. 3, pp. 3431–3448, 2024, doi: <https://doi.org/10.32604/cmc.2024.047604>
- [86] M. Hosseinzadeh, J. Khoramdel, Y. Borhani, and E. Najafi, “A New Fuzzy Logic Based Learning Rate Scheduling Method for Crop Classification With Convolutional Neural Network,” in *2022 8th International Conference on Control, Instrumentation and Automation (ICCIA)*, IEEE, Mar. 2022, pp. 1–5. doi: <https://doi.org/10.1109/ICCIA54998.2022.9737183>
- [87] D. Arockiam, A. Abdullah, and V. Raju, “Intelligent Crop Disease Detection and Classification Using Deep Convolution Neural Network with Honey Badger Algorithm on Image

- Data,” *Journal of Intelligent Systems and Internet of Things*, vol. 14, no. 2, pp. 178–188, 2025, doi: <https://doi.org/10.54216/JISIoT.140215>
- [88] D. Raja and M. Karthikeyan, “Red Deer Optimization with Deep Learning Enabled Agricultural Plant Disease Detection and Classification Model,” *International Journal of Intelligent Engineering and Systems*, vol. 16, no. 5, pp. 21–30, 2023, doi: <https://doi.org/10.22266/ijies2023.1031.03>
- [89] K. Kethineni and G. Pradeepini, “Identification of Leaf Disease Using Machine Learning Algorithm for Improving the Agricultural System,” *Journal of Advances in Information Technology*, vol. 14, no. 1, pp. 122–129, Feb. 2023, doi: <https://doi.org/10.12720/jait.14.1.122-129>
- [90] P. Dayang and A. S. Kouyim Meli, “Evaluation of Image Segmentation Algorithms for Plant Disease Detection,” *International Journal of Image, Graphics and Signal Processing*, vol. 13, no. 5, pp. 14–26, Oct. 2021, doi: <https://doi.org/10.5815/ijigsp.2021.05.02>
- [91] M. H. Nayeem, M. Newaz, A. K. Chakraborty, and A. Zaman Mamun, “Application of Image Processing for Plant Disease Identification Based on SVM Technique,” *International Journal of Engineering Trends and Technology*, vol. 68, no. 1, 2020, [Online]. Doi: <https://doi.org/10.14445/22315381/IJETT-V68I1P213>
- [92] A. Uppal, M. S. Naruka, and G. Tewari, “Image Processing based Plant Disease Detection and Classification,” *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 1, pp. 52–56, Jan. 2023. Available: <https://ijritcc.org>
- [93] S. K. Upadhyay and A. Kumar, “Early-Stage Brown Spot Disease Recognition in Paddy Using Image Processing and Deep Learning Techniques,” *Traitement du Signal*, vol. 38, no. 6, pp. 1755–1766, 2021, doi: <https://doi.org/10.18280/ts.380619>
- [94] T. M. Shahriar Sazzad, A. Anwar, M. Hasan, and M. I. Hossain, “An Image Processing Framework to Identify Rice Blast,” in *HORA 2020 - 2nd International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Proceedings*, Institute of Electrical and Electronics Engineers Inc., Jun. 2020. doi: <https://doi.org/10.1109/HORA49412.2020.9152912>
- [95] A. Hessane, A. El Youssefi, Y. Farhaoui, B. Aghoutane, and F. Amounas, “A machine learning based framework for a stage-wise classification of date palm white scale disease,” *Big Data Mining and Analytics*, vol. 6, no. 3, pp. 263–272, 2023. doi: <https://doi.org/10.26599/BDMA.2022.9020022>
- [96] S. Chaudhary and U. Kumar, “Analysis of Methods of Machine Learning Techniques for Detection and Classification of Brown Spot (Rice) Disease,” *Univers. J. Agric. Res.*, vol. 10, no. 5, pp. 464–473, Oct. 2022, doi: <https://doi.org/10.13189/ujar.2022.100502>
- [97] A. Chaudhary, V. Kumar, and R. K. Chaturvedi, “PROBABILITY BASED CLASSIFICATION METHOD FOR PLANT DISEASE DETECTION Article Information,” *Original Research Article Plant Cell Biotechnology and Molecular Biology*, vol. 21, no. 58, pp. 22–31, 2020. Available: <https://hal.science/hal-05270372>
- [98] X. Li et al., “A bio-inspired framework for apple leaf disease detection: Integrating lesion localization, ant colony optimization, and machine learning,” *Smart Agricultural Technology*, vol. 12, Dec. 2025, doi: <https://doi.org/10.1016/j.atech.2025.101141>
- [99] A. Jain and R. K. Dwivedi, “Hybrid segmentation-based agricultural leaf disease detection (Hy-SALDD) using black widow optimization for feature selection, and Bayesian-optimized SVM classification,” *International Journal of Information Technology (Singapore)*, vol. 17, no. 6, pp. 3197–3211, Jul. 2025, doi: <https://doi.org/10.1007/s41870-025-02478-0>
- [100] U. Muthaiah and S. Chitra, “Mango Pest Detection Using Entropy-ELM with Whale Optimization Algorithm,” *Intelligent Automation and Soft Computing*, vol. 35, no. 3, pp. 3447–3458, 2023, doi: <https://doi.org/10.32604/iasc.2023.028869>
- [101] M. K. Priyadarshini, R. Sivakami, and M. Janani, “Sooty mould mango disease identification using deep learning,” *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 8, no. 5S, 2019. Available: <https://www.ijitee.org/portfolio-item/ES3452018319/>
- [102] A. Ștefania Stanciu, T. Rusu, A. C. Teușdea, O. S. Mintăș, M. M. Cărbunar, and C. Oneț, “Digital image processing in determining the degree of turnip yellows virus infection in oilseed rape,” *Turkish Journal of Agriculture and Forestry*, vol. 49, no. 2, pp. 356–379, 2025, doi: <https://doi.org/10.55730/1300-011X.3271>