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Computer Vision for Plant Disease Recognition: A Comprehensive Review

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Abstract

Agriculture has undergone a remarkable transformation, transitioning from traditional methods that were used for centuries to technology-driven practices. The advent of image processing and computational intelligence has revolutionized crop production and plant health monitoring. From drones capturing detailed crop growth data to sensors meticulously measuring soil moisture levels, the possibilities are boundless. This review delves into the cutting-edge research advancements in the application of image processing and computational intelligence techniques for botanical fields, with a particular focus on plant health monitoring. First, it provides a comprehensive overview of the diverse imaging sensors employed in agriculture, including visible, near-infrared, thermal, and hyperspectral imaging. Subsequently, it carefully analyzes the advantages and limitations of each sensor type, along with illustrative examples of their utilization in plant health monitoring. The review further explores the application of machine learning and deep learning for automated plant disease identification, highlighting the critical need for standardized datasets, benchmarking protocols, and domain-specific knowledge for effective implementation. In conclusion, the review emphasizes the future challenges and trends in this rapidly evolving field. It serves as a valuable resource, providing insights into the latest trends in computer vision-based plant disease monitoring and identifying gaps that demand further attention from the scientific community.

Keywords Plant disease · Precision agriculture · Image processing · Phytopathology · Deep learning · Disease recognition

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Introduction

As a cornerstone of the global economy, agriculture plays a pivotal role in ensuring food security and meeting the nutritional needs of an ever-expanding population Velten et al. (2015). However, the agricultural sector faces a numerous complex challenges, with crop diseases emerging as a significant barrier to achieving sustainable agricultural practices. Effective disease management and control measures are paramount to minimizing production losses and safeguarding crop sustainability, as emphasized by Ristaino et al. (2021). Phytopathologists widely advocate for regular crop monitoring and accurate disease diagnosis as essential practices for mitigating the impact of plant diseases, maintaining crop health, and promoting sustainable agricultural practices Huang et al. (2019). These measures are crucial for ensuring a resilient and productive agricultural sector capable of meeting the food demands of a growing population Edwards (2020).

Accurately detecting plant diseases is essential for maintaining optimal crop health and productivity. Traditional methods of disease recognition and monitoring are often labor-intensive, time-consuming, and prone to inaccuracies, often leading to delayed interventions and reduced crop yields Lowenberg-DeBoer and Erickson (2019). However, the advent of image processing Liakos et al. (2018) and computational intelligence techniques Minh et al. (2022) has revolutionized the field of plant disease detection, offering a rapid, precise, and cost-effective approach to disease management Idoje et al. (2021). These advanced technologies enable the extraction of valuable information from crop images, including leaf color, texture, and shape, which serve as telltale signs of disease presence. Moreover, computational intelligence algorithms, such as machine learning (ML) and deep learning (DL), provide powerful tools for analyzing image data and making accurate predictions on disease occurrence and severity. By integrating image processing and computational intelligence, researchers and farmers can develop automated and effective systems for early detection and analysis of plant diseases Ubbens and Stavness (2017). These innovative technologies have the potential to transform crop management practices, optimize resource utilization, and ultimately enhance agricultural productivity and food security Moysiadis et al. (2021).

In the field of plant disease detection, a standardized framework typically comprises four fundamental components, as illustrated in Fig. 1. These components collaborate harmoniously to achieve accurate and efficient disease identification Liu and Wang (2021); Abade et al. (2021). The first component is data collection, which involves utilizing various vision sensors to gather relevant information from plants. These sensors capture images or other forms of visual data that can be analyzed for disease detection. Once collected, the data undergoes image pre-processing, a crucial step that encompasses procedures such as resizing, filtering, and color space conversion to enhance image quality and consistency. The pre-processed data is then fed into the plant disease recognition component, where ML/DL models take center stage. These models are trained to recognize patterns and features within the collected data, enabling them to accurately identify and classify different plant diseases. Finally, the performance and effectiveness of the plant disease identification models are thoroughly evaluated to assess their reliability and potential for real-world applications. By employing this

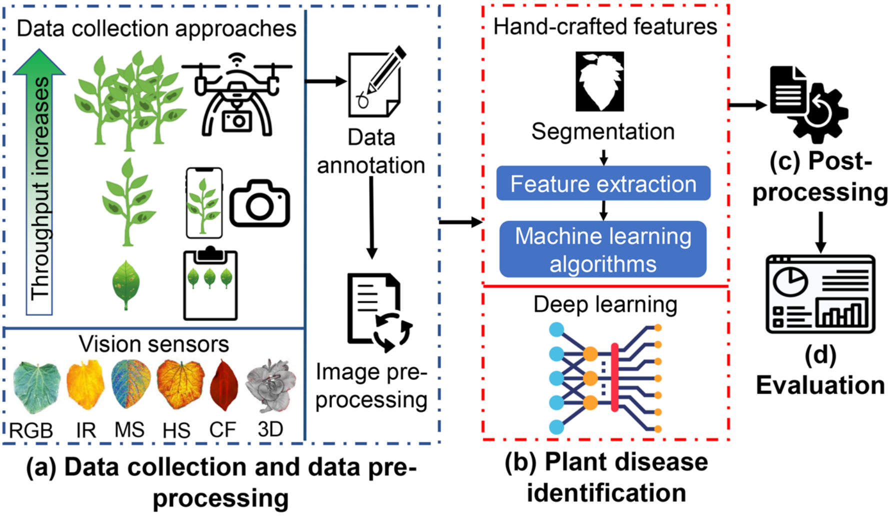


Fig. 1 A typical plant disease recognition framework consists of four key agents, (a) data collection and data pre-processing, involving the use of diverse vision sensors to gather relevant data and the implmentation of crucial pre-processing procedures on the collected data; (b) plant disease recognition, where ML or DL models are employed to recognize patterns within the collected data; (c) post-processing; and (d) evaluation, which assesses the performance and effectiveness of the plant disease recognition models, **Note:** Common vision sensors include red, green, blue (RGB), infrared (IR), multispectral (MS), hyperspectral (HS), chlorophyll fluorescence (CF), and three-dimensional sensing (3D)

comprehensive framework, researchers and practitioners can streamline the process of plant disease recognition and contribute to the development of effective solutions for disease management in agriculture.

This comprehensive survey aims to summarize, categorize, and analyze recent advancements in computer vision-based plant disease identification. It provides an in-depth overview of various components, including feature extraction, segmentation, and classification algorithms employed for traditional disease detection methods. Subsequently, the survey systematically categorizes and compares previous DL-based plant disease detection research, highlighting the strengths and limitations of each approach. Additionally, it delves into the challenges and limitations associated with these methods, such as dataset availability, model generalization, and real-time deployment. To further guide future research, the survey identifies potential research directions and emerging trends in phytopathology, aiming to inspire further advancements in plant disease identification. By consolidating and synthesizing knowledge and findings from a wide range of studies, this survey serves as an invaluable resource for researchers, practitioners, and stakeholders interested in monitoring and managing plant diseases.

Review Strategy

This review focuses on digital scientific databases and excludes any gray literature from the investigation process. This exclusion is based on the assumption that most relevant research in the gray literature (reports, theses, dissertations, conference proceedings, working papers, government documents, and other materials) is already referenced in published scientific papers. To identify primary studies, a search and selection strategy was implemented across five indexed electronic databases: Elsevier Scopus, ACM Library, IEEE Xplore Digital Library, and Google Scholar. These databases were selected for their comprehensive coverage of high-ranking scientific conference proceedings and journals within the plant disease detection sector.

To gather relevant literature efficiently, a search string was formulated based on the key terms related to the topic of plant disease recognition. While each indexed research portal has its own syntax for constructing search strings, a generic string was initially defined and then customized for each search engine. The search string used in this study was as follows: (“plant disease” OR “plant pathology” OR “crop disease”) AND (“machine learning” OR “convolutional neural network” OR “deep learning” OR “DNN” OR “CNN”). The search string included synonyms for plant disease to ensure that all relevant studies were captured. Additionally, the string included terms related to ML and DL to focus on studies that used these techniques for plant disease recognition.

The past decade has witnessed a surge of interest within the scientific community in harnessing the power of image processing and computational intelligence for plant disease detection and recognition. To capture the most recent advancements, this review exclusively considered publications published between 2013 and 2023. The search string was intentionally crafted to cover a wide range of literature, safeguarding against the inadvertent omission of potentially impactful research. This resulted in the retrieval of a substantial number of papers, followed by a rigorous filtering process based on the following selection criteria to identify the most relevant contributions.

- Include: Research focusing on the utilization of ML/DL for plant disease recognition.
- Include: Research introducing novel ML/DL models or architectures related to plant disease recognition.
- Include: Research presenting novel techniques or methods for plant disease recognition.
- Exclude: Research not written in English.
- Exclude: Duplicate studies from multiple websites.

Figure 2 provides an overview of the current research landscape on disease identification across different crops. While there are numerous crops that could be considered for a comprehensive review of plant disease identification, the selection of crops in these studies is influenced by the availability of datasets and expert knowledge. A total of 121 studies were analyzed to generate the plant distribution chart. The chart highlights that a significant portion of recent studies relied on the PlantVillage dataset Hughes et al. (2015) for conducting experiments. Additionally, there is a notable increase in interest in phytopathology, particularly focusing on fruits, such as tomatoes, grapes, and apples.

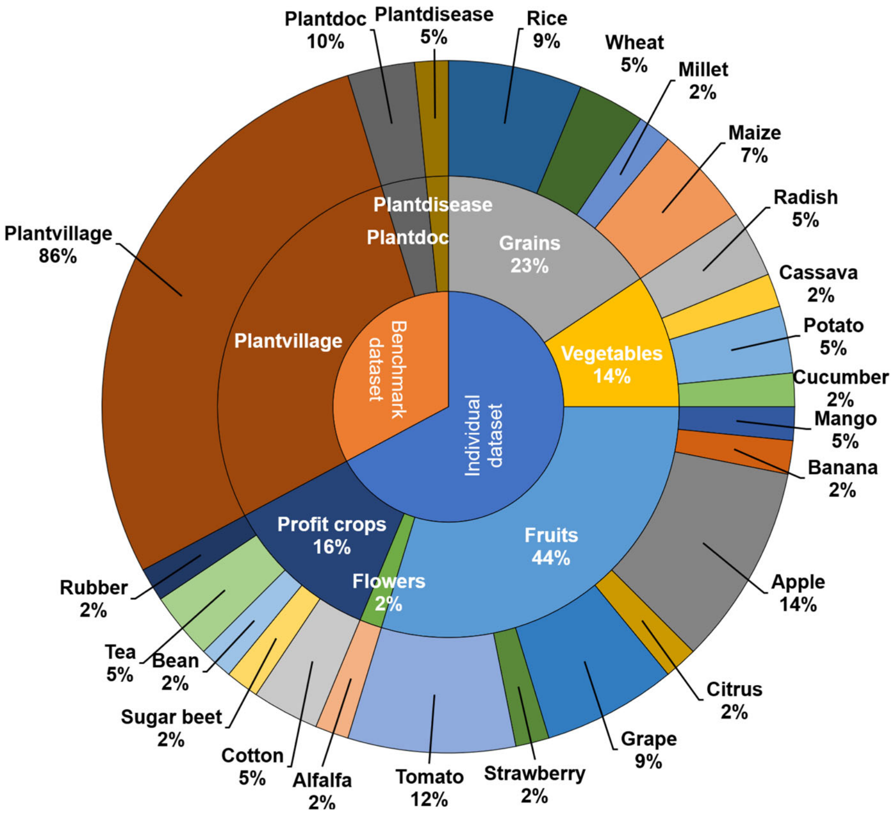


Fig. 2 The current disease detection research landscape in various plants over the past decade (percentage of papers)

Relevant Reviews

This paper aims to provide a systematic categorization and discussion of the latest studies on plant diseases. It also extensively examines the challenges and future research directions for plant disease recognition studies. A summary of previous surveys on this topic is presented in Table 1. While Wani et al. (2022); Thakur et al. (2022); Jackulin and Murugavalli (2022) primarily focus on common ML and DL models for disease classification; Liu and Wang (2021); Li et al. (2021); Shoaib et al. (2023) mainly work on analyzing previous plant disease detection studies, our survey categorizes and discusses ML/DL models for various disease classification/detection/segmentation approaches, providing a comprehensive comparison of disease recognition research across multiple crops. This broader perspective enables a more holistic understanding of the different approaches and their suitability for different crops.

Other references, such as Vishnoi et al. (2021); Sinha and Shekhawat (2020); Nagaraju and Chawla (2020), delve into various aspects of plant disease detection using ML/DL methods, our study distinguishes itself by providing a comprehensive

Table 1 Overview of related work and our survey

Reference	Main contribution	How our survey differ
Wani et al. (2022)	• Discuss common ML and DL models for disease classification • Present disease classification studies for tomato, rice, potato, and apple	• Categorize and discuss ML and DL models for previous plant disease classification, detection, and segmentation studies • Compare disease identification research for various benchmark datasets
Thakur et al. (2022)	• Briefly discuss data processing for traditional ML-based plant disease classification • Focus on analyzing DL-based plant disease classification	
Jackulin and Murugavalli (2022)	• Review 7 ML models and 3 DL models for various plant disease classification • Compare ML and DL models	
Vishnoi et al. (2021); Sinha and Shekhawat (2020)	Discuss the use of image pre-processing and ML methods for plant disease detection	• Discuss latest image processing techniques • Categorize and analyze hand-crafted feature extraction and DL approaches
Liu and Wang (2021); Abade et al. (2021); Li et al. (2021)	Focus on standard DL techniques used for plant disease detection (leaf, pest)	Categorize and compare traditional ML and DL methods for plant disease identification
Shoaib et al. (2023)	Discuss existing challenges and recent advancements in DL-based plant disease detection between 2015 and 2022	
Nagaraju and Chawla (2020)	Compare 18 DL-based disease identification research (2015-2018)	Compare 16 ML-based and 46 DL-based plant disease identification research (2016-2023)
Saleem et al. (2019); Zhang et al. (2019a); Golhani et al. (2018)	Concentrate on remote sensing with DL methods for plant disease identification	Describe and analyze plant disease detection using various vision sensors

analysis of the latest image processing techniques, involving both hand-crafted feature extraction approaches and DL approaches. We also conduct a comparative analysis of original techniques and DL techniques for plant disease detection, offering insights into the advancements in the field. References like Saleem et al. (2019); Zhang et al. (2019a); Golhani et al. (2018) primarily focus on remote sensing and the use of DL models for plant disease detection. In contrast, our survey goes beyond remote sensing and explores the utilization of various vision sensors, including RGB, hyperspectral, multispectral, and infrared, for plant disease detection. This broader coverage allows us to analyze and describe the application of different sensors in plant disease detection, providing a more comprehensive overview of the field.

This survey fills the gap by providing a comprehensive categorization, comparison, and analysis of ML/DL models, image processing techniques, and sensor utilization for plant disease identification. It distinguishes itself from previous works that have primarily focused on specific crops, limited techniques, or remote sensing alone. The contributions of the survey are as follows.

- First, they survey offer a concise overview of the background related to data collection, image processing, and computational intelligence methods in the context of plant disease recognition. This essential foundation ensures that readers are well-versed in the latest state-of-the-art developments in this field.
- Next, it delves into a detailed categorization and discussion of the recent advancements in plant disease recognition that utilize image processing and computational intelligence techniques. By organizing the literature based on these categories, readers gain valuable insights into the latest approaches and methodologies. This exploration not only empowers crop monitoring applications but also contributes to the overall understanding of plant disease recognition.
- Finally, the survey outlines future research directions to guide and inspire further studies in the application of image processing and computational intelligence for plant disease detection. By identifying key areas for future investigation, the survey aims to drive advancements and foster innovation in the field of plant disease detection, equipping researchers with an in-depth understanding of the existing challenges and future directions for this sector.

The remainder of this survey is organized as follows. Section 2 lays a solid foundation by providing an overview of the core concepts in plant disease recognition. Section 4 then delves into the different types of plant disease detection architectures commonly employed, with a particular focus on the traditional handcrafted feature extraction approach. After that, Section 5 focuses on analyzing various aspects of DL-based plant disease detection, highlighting its strengths and limitations. To assess the effectiveness of these approaches, Section 3 presents the benchmark datasets and common evaluation metrics used for plant disease detection. Finally, Section 6 outlines the challenges and future directions that lie ahead for this rapidly evolving field, while Section 7 draws comprehensive conclusions and emphasizes the significance of these advancements in crop management.

Background

Plant Diseases

Plant diseases pose a significant threat to agriculture and horticulture, with the potential to cause devastating damage to crops and lead to substantial economic losses. These diseases include a wide spectrum of abnormalities in plants, manifesting as physiological, morphological, and behavioral changes that detrimentally impact their growth, development, and productivity. As illustrated in Fig. 3, the causes of these diseases can be diverse, ranging from living organisms (biotic stress) such as fungi, bacteria, viruses, nematodes, and phytoplasmas to non-living factors (abiotic stress) such as environmental conditions, nutrient deficiencies, chemical imbalances, and physical injuries .

Infectious plant diseases, caused by living pathogens, pose a significant threat to agriculture and horticulture due to their ability to rapidly spread within plant populations, resulting in widespread outbreaks and epidemics Teshome et al. (2020). These diseases can be transmitted through various means, including air, soil, water, and vectors like insects and other animals. Once inside the plant, pathogens invade its tissues, disrupting its normal functioning and leading to a wide range of symptoms, such as wilting Dang et al. (2020b), leaf spots Barbedo (2019); Liang (2021), lesions Barbedo (2019); Ngugi et al. (2021), stunting, discoloration, and even plant death OBrien (2017). Given the typically milder nature of abiotic diseases due to their non-

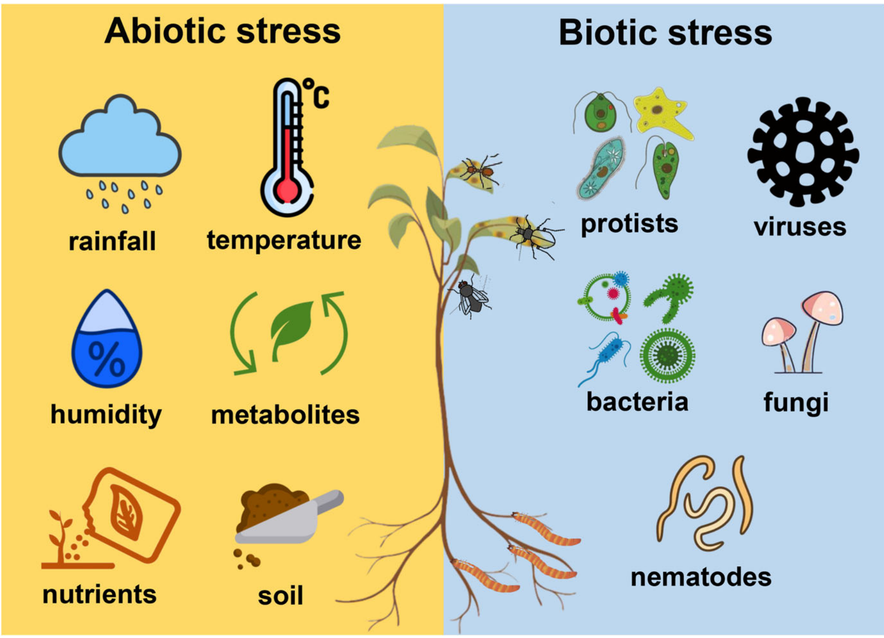


Fig. 3 Visualization of abiotic and biotic stresses that cause plant disease

transmissible characteristics and relative stability over time Fujita et al. (2006), this survey primarily focuses on biotic diseases.

Within the field of phytopathology, the literature often addresses diseases like blight Su et al. (2020) (fungal or bacterial disease that causes discoloration and lesions on plant tissues), mildew Shin et al. (2021) (fungal disease that covers plant leaves with a white, powdery substance), rust Deng et al. (2022) (fungal disease that causes reddish-brown pustules on plant leaves), spots Barbedo (2019) (caused by fungi or bacteria), and canker Syed-Ab-Rahman et al. (2022) (fungal or bacterial disease that causes sunken lesions on plant stems and branches), which are regarded as the most prevalent Jayawardena et al. (2021).

Efficient management and control of plant diseases are crucial for ensuring crop health, maximizing yields, and maintaining food security. Early detection, accurate diagnosis, and timely implementation of appropriate disease management strategies are essential for minimizing the impact of plant diseases Thurston (2019). Advances in technology, such as imaging sensors, image processing, and computational intelligence, have provided new opportunities for the development of automated plant disease detection and diagnosis systems, facilitating prompt and effective disease management practices.

Computer Vision (CV)-Based Plant Disease Detection

Traditional methods of detecting and diagnosing plant diseases, such as visual inspection by human experts, can be time-consuming, expensive, and subjective Barbedo (2018). This can lead to delayed treatment and increased crop losses. CV-based plant disease detection is an emerging field that combines the power of CV techniques with the domain of plant pathology. It aims to develop automated systems that can accurately identify and diagnose diseases in plants by analyzing visual information captured through images or videos Chouhan et al. (2020). CV provides a promising solution to these challenges by leveraging image processing algorithms, pattern recognition techniques, and ML/DL models .

By analyzing crop images, CV algorithms can effectively detect and classify disease symptoms, leaf discoloration, lesions, or other visual cues associated with specific diseases Sun et al. (2018).

Traditionally, identifying signs of disease in plants has involved capturing and analyzing digital images. These images undergo pre-processing, which includes filtering, enhancement, and segmentation to prepare them for further analysis. Next, feature extraction methods are employed to extract relevant information from the images, such as the color, texture, and shape of plant parts. Finally, ML algorithms are trained on these extracted features to distinguish between healthy and diseased plant samples. The output of this image processing pipeline can generate reports for farmers, assisting them in making informed decisions about crop management practices, such as pesticide application or irrigation scheduling. Advancements in CV techniques, along with the accessibility of large-scale image datasets and improvements in hardware capabilities, have driven the development of sophisticated disease detection models. DL models, such as convolutional neural networks (CNNs), have demonstrated remarkable performance in plant disease recognition, surpassing human-level accuracy in some cases Li et al. (2021); Liu and Wang (2021). These algorithms can learn from labeled training data, enabling them to generalize and accurately identify diseases in unseen plant samples.

CV-based plant disease identification holds the potential to transform the agricultural industry by facilitating early and accurate disease diagnosis, enabling timely intervention, and empowering effective management strategies Tian et al. (2020b). This technology can significantly contribute to minimizing crop losses, optimizing resource utilization, and promoting sustainable farming practices. Ongoing research in this field focuses on enhancing the accuracy, scalability, and real-time capabilities of these systems, making them accessible and practical for farmers worldwide. By developing more robust algorithms, integrating advanced sensing technologies, and leveraging the power of ML/DL models, CV-based plant disease detection systems can be tailored to meet the specific needs and challenges of diverse agricultural environments. The ultimate goal is to empower farmers with efficient tools that enable them to make informed decisions, prevent disease outbreaks, and optimize crop health and productivity, ensuring a more sustainable and productive agricultural landscape.

Data Collection and Data Pre-Processing

Data Collection

Data collection for plant disease recognition using various vision sensors involves employing imaging technologies to capture visual information about plants and their associated diseases. Vision sensors, including RGB, hyperspectral, multispectral, infrared (IR), and fluorescence sensors, enable the collection of detailed and specific data pertaining to plant health and disease symptoms Singh et al. (2020b). Table 2 provides a comparison of common vision sensors employed for plant disease recognition.

The detailed description of some of the common vision sensors is as follows.

- RGB sensors are widely used in plant disease data collection due to their ability to capture red, green, and blue color channels, providing valuable information about the color, shape, and visual appearance of plants Dang et al. (2020b); Shin et al. (2021). These sensors are particularly effective in detecting visible symptoms such as discoloration, spots, lesions, and deformities caused by diseases. Their widespread availability, cost-effectiveness, and non-destructive nature make them a popular choice for various plant disease detection applications.
- Hyperspectral and multispectral sensors offer enhanced capabilities compared to RGB sensors by capturing images in multiple narrow bands across the electromagnetic spectrum. Hyperspectral sensors capture images in a vast number of spectral bands, enabling detailed spectral analysis of plant tissues and facilitating the detection of subtle changes in plant physiology and the early detection of diseases Golhani et al. (2018). In contrast, multispectral sensors capture images in a smaller number of predetermined spectral bands, providing a more cost-effective

Table 2 Comparison of common vision sensors for collecting data for plant disease recognition

Sensor type	Wavelength range	Spatial resolution	Advantages	Disadvantages
RGB	Visible (400-700 nm)	3	Low-cost, widely available	Limited spectral information
IR	Spectral (700-1000 nm)	1	Detect physiological changes, non-invasive	Limited spectral information, expensive
Multispectral	Visible and spectral (400-1000 nm)	>3	Improved spectral resolution, capture both visible and NIR light	Expensive, limited spectral range
Hyperspectral	Visible and spectral (400-2500 nm)	>10	High spectral resolution, capture both visible and NIR light	Expensive, complex data processing
Fluorescence	Visible and ultraviolet (300-700 nm)	Multiple	Sensitive to plant stress, non-invasive	Limited spectral range, specialized equipment
3D	Visible (400-700 nm)	N/A	Capture plant morphology, non-invasive	Limited spectral information

approach while still offering valuable information about plant health and disease Kerkech et al. (2020).

- Infrared sensors, equipped with the ability to detect and measure infrared radiation emitted by objects, hold immense potential in assessing plant health by identifying subtle temperature variations Nouri et al. (2018). These sensors prove particularly valuable in detecting stress-related diseases and monitoring the water status of plants.
- Harnessing the principle of fluorescence emission, fluorescence sensors provide a sophisticated tool for evaluating plant health and physiological status. By illuminating plants with specific wavelengths of light, these sensors trigger the excitation of fluorescent compounds within the plant's tissue Pérez-Bueno et al. (2019). The emitted fluorescence is then captured by the sensor, and its intensity and spectral characteristics provide valuable insights into the presence and severity of plant diseases. With their ability to detect subtle changes in plant metabolism, chlorophyll content, and stress responses, fluorescence sensors enable early disease detection and targeted treatment strategies.
- 3D sensors, empowered by depth-sensing technology, revolutionize plant health assessment by capturing intricate three-dimensional information about plants Nagasubramanian et al. (2019). These cameras employ advanced techniques like structured light or time-of-flight measurements to accurately estimate the distance between the camera and various points on the plant surface. By meticulously reconstructing the plant's shape and structure in three dimensions, 3D cameras enable precise measurements of crucial plant features, including leaf area, plant height, and canopy density. This detailed information proves invaluable in assessing plant health, identifying early signs of disease, and monitoring the growth and development of crops with unparalleled precision.

Data collection using these vision sensors typically involves capturing images of plants in various environmental conditions and growth stages. The collected images are then processed and analyzed using image processing techniques, ML/DL algorithms, and computational intelligence methods to extract relevant features and patterns associated with plant diseases.

Data Pre-Processing

Data Annotation

Data annotation for plant disease detection is a process that involves labeling and categorizing plant images to train ML/DL models for accurate identification and diagnosis of plant diseases Emam et al. (2021). In this context, a diverse and comprehensive dataset consisting of images of both healthy and diseased plants. Each image must be carefully annotated with precise labels that indicate the presence or absence of plant diseases, pinpointing the affected regions within the images. This labeling process ensures that ML/DL models can effectively learn to distinguish between healthy and diseased plants, enabling accurate disease detection and diagnosis.

The data annotation process for plant disease detection demands the full participation of pathologists, whose specialized knowledge and keen eye for disease symptoms are indispensable in carefully verifying and annotating images, therefore ensuring the accuracy and high quality of the training dataset Dong et al. (2022). Pathologists' expertise is imperative in distinguishing between various diseases, enabling annotated data to accurately reflect the diverse symptoms of plant pathogens Pagán and García-Arenal (2020). Their contributions extend beyond the precision of image annotations, as they closely collaborate with CV experts to refine the annotation process and provide invaluable insights into the unique features and subtle variations associated with different diseases. This cooperation effort enhances the robustness and accuracy of ML/DL models, guaranteeing that they are trained with datasets that faithfully capture the complexity of real-world plant disease scenarios.

Data annotation for plant disease detection can take various forms, including bounding boxes, segmentation masks, or classification labels, depending on the specific requirements of the ML/DL model. Bounding boxes efficiently highlight the areas of interest within an image Wang et al. (2022), while segmentation masks precisely outline the boundaries of affected regions, providing a more detailed representation of disease symptoms Deenan et al. (2020). Classification labels, on the other hand, assign categories such as "healthy" or specific disease names to each image, facilitating broad-level disease classification Azim et al. (2021). Expert annotators or domain specialists play a pivotal role in this process, leveraging their knowledge and expertise to accurately identify and mark disease symptoms in the images. Their detailed annotations ensure that ML/DL models are trained with high-quality data, enabling accurate disease detection and diagnosis. Some popular data annotation tools for plant disease detection are as follows.

- VGG Image annotator (VIA) Dutta and Zisserman (2019): VIA is a free and open-source tool for image annotation based on HyperText Markup Language (HTML). This reliance on HTML eliminates the need for external libraries, resulting in a lightweight and feature-rich manual annotation software that can run on most modern web browsers without any installation or setup. VIA's user-friendly interface facilitates the creation of bounding boxes, segmentation masks, and classification labels, making it a valuable tool for developing ML/DL models.
- LabelImg LabelIm (2018): LabelImg is a freely available and open-source graphical image annotation tool specifically designed for labeling and categorizing images to train ML/DL models. Its extensive range of applications spans various fields, including object detection and image classification. LabelImg supports a user-friendly interface equipped with intuitive controls, making it readily accessible to users with varying levels of technical expertise.
- LabelMe Russell et al. (2008): LabelMe is a free and open-source tool for image annotation that has gained popularity in generating annotations for plant disease segmentation tasks. It supports various annotation formats, including polygons, rectangles, circles, lines, and points, catering to diverse annotation needs. While LabelMe shares similarities in functionality with VIA, it offers additional features, such as importing images directly from URLs and exporting annotations in various formats, enhancing its versatility and usability.

- COCOAnnotator Brooks (2019): COCOAnnotator is a web-based annotation tool that streamlines image annotation without requiring any installation. It offers a suite of distinct features including labeling individual image segments or portions of a segment, tracking object instances, annotating objects with disconnected visible parts, and efficiently storing and exporting annotations in the widely recognized COCO format.

Quality control measures are crucial to maintaining the accuracy and consistency of the annotated dataset. Regularly reviewing the annotated data and monitoring inter-annotator agreement help ensure the reliability of the annotations. To facilitate effective model training, evaluation, and testing, the annotated dataset is typically divided into training, validation, and test sets. This iterative approach to data annotation allows for continuous improvement as the model evolves. Additional annotated data may be needed to refine the plant disease detection model, ensuring its effectiveness and adaptability.

Image Pre-Processing

Image pre-processing is a pivotal step in plant disease detection, ensuring the quality and suitability of images for subsequent analysis Tabik et al. (2017). This critical stage involves applying mathematical and statistical techniques to enhance the visual appearance and geometric characteristics of an image, transforming it into a standardized format suitable for analysis. Images often face challenges such as shadows, distortion, noise, and complex backgrounds. Pre-processing addresses these issues, improving image quality and making them more appropriate to further processing. Real-life datasets often contain irrelevant or inappropriate information, necessitating pre-processing to enhance computational accuracy in disease detection systems. Pre-processing operations such as resizing and cropping can also reduce processing time while maintaining system performance Huang et al. (2017).

Among the fundamental pre-processing techniques, image resizing stands out as a crucial step. By standardizing the image dimensions across the dataset, resizing ensures consistency and facilitates efficient feature extraction and model training. This standardization eliminates the variability in image sizes, allowing the model to focus on the relevant features rather than the differences in image dimensions Pavel et al. (2019). Noise removal techniques are also essential in enhancing the quality of plant images for disease detection. Various types of noise, such as Gaussian noise or salt-and-pepper noise, can obscure important details and hinder accurate analysis. Noise reduction techniques, such as median filtering or adaptive filtering, effectively eliminate these noise artifacts, thereby improving the clarity of the images and enabling better detection and analysis of disease symptoms Tian et al. (2020a). Contrast enhancement techniques are another valuable tool in the pre-processing pipeline. By adjusting the image contrast, subtle variations in color and texture become more discernible, facilitating the identification of disease symptoms. Histogram equalization Dhal et al. (2021) and contrast stretching Rehman et al. (2021) are two common contrast enhancement methods that can significantly improve the visibility of fine-grained details, making them particularly beneficial for accurate classification of plant diseases. Color normalization techniques address the issue of varying lighting conditions and camera settings, which can introduce inconsistencies in the color representation of images. By converting images to a standardized color space, such as Lab or hue, saturation, value (HSV), or applying histogram matching, color variations are minimized, leading to more consistent and reliable feature extraction and analysis. Figure 4(a) illustrates the application of various pre-processing techniques on two input leaf images.

In addition to contrast and color adjustments, image filtering techniques play a crucial role in enhancing the quality of plant images for disease detection. Edge detection filters, such as Sobel or Canny Ahmed (2018), sharpen the edges of objects in the images, making it easier to distinguish between plant parts and the background. This edge enhancement facilitates segmentation of regions of interest (ROIs) for disease detection. Frequency-based filters, such as Gaussian or Laplacian filters Wang et al. (2020), serve specific purposes in image pre-processing. Gaussian filters effectively smooth out noise in the images, while Laplacian filters emphasize specific image features, such as edges or textures. By applying appropriate filters, image pre-processing enhances the overall image quality and ensures that the subsequent analysis can be carried out effectively and accurately for plant disease detection.

Benchmark Dataset

Currently, several widely used datasets offer a diverse collection of images depicting diseases in various plant species. While some datasets are private, a significant portion is freely accessible to researchers. These open-source datasets serve as valuable resources for training, evaluating, and comparing the performance of ML-based disease detection studies within the research community. Figure 5 showcases sample images from three widely used plant disease datasets: PlantVillage Hughes et al. (2015), PlantDoc Singh et al. (2020a), and Plant pathology challenge 2021 Thapa et al. (2020). These datasets, encompassing a diverse range of plant species and disease conditions, are valuable resources for training and evaluating machine learning

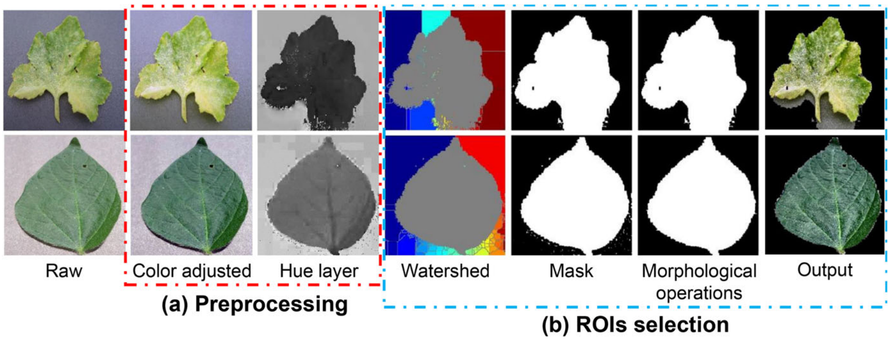


Fig. 4 Important methods for pre-processing and ROIs selection on two sample images by Ahmad et al. (2021)

Fig. 5 Sample plant disease images from popular PlantVillage, PlantDoc, and Plant pathology challenge 2021 datasets

models for plant disease detection. They can be freely downloaded from the following links:

- PlantVillage[1]
- PlantDoc[2]
- Plant pathology challenge 2021[3]

Table 3 offers a comprehensive overview of commonly used plant disease detection datasets. The datasets included in the table span from 2015 to 2023. There are variations in the number of plant species, disease classes, and total images across the datasets. Notably, the plant disease dataset 271 (PDD271) and plant disease diagnosis dataset (PDDD) datasets stand out as the largest and most comprehensive datasets. PDD271 Liu et al. (2021) covers a wide range of plants with 271 disease classes and over 220,000 RGB images. PDDD Dong et al. (2023), on the other hand, contains 120 disease classes and approximately 421,133 images. The authors of the PDDD dataset also provide 50 pre-trained models[4] trained using standard DL models on the PDDD datasets.

The PlantVillage dataset Hughes et al. (2015) stands as a widely recognized and extensively utilized resource in the field of plant disease detection. This comprehensive dataset offers a diverse collection of high-quality images representing multiple plant species affected by various diseases. Its images are captured under different lighting conditions, angles, and magnifications, effectively mimicking real-world scenarios and enhancing its generalizability. With 54,305 RGB images of size 256 $\times$ 256, the dataset include 14 plant species: apples, blueberries, cherries, corn, grapes, oranges, peaches, peppers, potatoes, pumpkins, raspberries, soybeans, strawberries, and tomatoes. Among these species, 17 are affected by fungal diseases, 4 by bacterial diseases, 2 by both fungal and viral diseases, and 1 by diseases caused by mites. Additionally,

1 https://plantvillage.psu.edu/posts/6948-plantvillage-dataset-download

2 https://github.com/pratikkayal/PlantDoc-Dataset

3 https://www.kaggle.com/c/plant-pathology-2021-fgvc8/discussion/243042

4 https://pd.samlab.cn/download.html

Table 3 Comparison of common plant disease detection datasets for all types of sensors

Dataset name	Year	Sensor type	# species	# classes	# images
PDDD Dong et al. (2023)	2023	RGB	14	120	421,133
Plant pathology challenge Thapa et al. (2020)	2021	RGB	Apple	12	23,000
PDD271 Liu et al. (2021)	2021	RGB	42	271	220,592
Turkey-Plant Sutaji and Yıldız (2022)	2021	RGB	-	15	4447
AI2018 Yu et al. (2023)	2020	RGB	10	61	44,929
Rice diseases image Huy (2020)	2020	RGB	Rice	4	5,447
PlantDoc Singh et al. (2020a)	2020	RGB	13	27	2,598
Soybean 3D dataset Nagasubramanian et al. (2019)	2019	3D	Soybean	2	1,823
Kaggle cassava disease Mwebaze et al. (2019)	2019	RGB	Cassava	5	9,436
PlantDisease Arsenovic et al. (2019)	2019	RGB	12	42	79,265
New plant diseasesBhattarai (2018)	2018	RGB	14	38	87,000
Hyperspectral dataset for apple scab disease detection Nouri et al. (2018)	2018	Hyperspectral	Apple	2	Na
PlantVillage Hughes et al. (2015)	2015	RGB	14	38	54,305

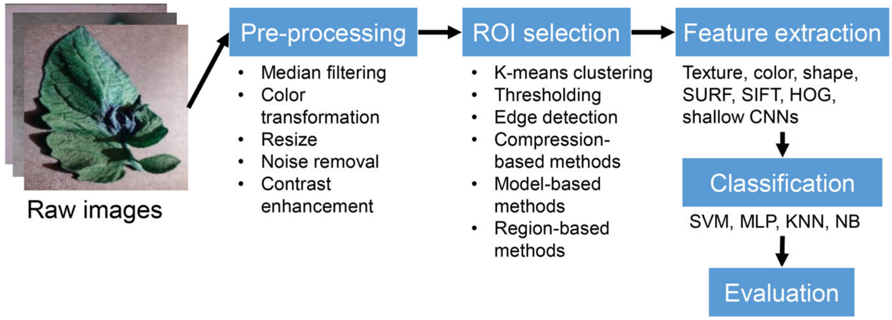


Fig. 6 Overview of important steps for traditional plant disease detection approach

there are 12 plant species classified as healthy leaves. Due to its extensive usage, reliability, and comprehensive coverage of various plant species and disease types, the PlantVillage dataset has become a standard benchmark for evaluating the performance of plant disease recognition algorithms and models.

In addition to the datasets listed in Table 3, several research centers maintain valuable collections of plant disease images. These include the IPM database[5], which offers a diverse collection of images representing various plant diseases and pests, the UCI Machine Learning Repository's Rice Leaf Diseases dataset[6], which provides images of rice leaves affected by various diseases, the Kaggle New Plant Diseases Dataset[7], which contains images of tomato leaves affected by various diseases, and the American Phytopathological Society (APS) Image Database[8], which offers a curated collection of high-resolution images of plant diseases.

Traditional Plant Disease Detection Approach

Figure 6 describes a typical workflow for early work in plant disease detection, which mainly relies on the hand-crafted features. Hand-crafted feature extraction for plant disease detection involves several important components. Some of the key components are as follows.

- ROI selection: In plant disease detection, focusing on specific ROIs where disease symptoms are more prominent is crucial for efficient and accurate analysis. It involves isolating and segmenting the relevant plant parts from the background using techniques like thresholding, edge detection, or clustering. By narrowing down the analysis to these targeted areas, the computational burden is reduced, and the focus is shifted to the most informative regions for disease identification.
- Feature extraction: Following the identification of the ROI, feature extraction plays a crucial role in capturing the essence of the plant disease. This process involves

[5] https://www.ipmimages.org/index.cfm

[6] https://archive.ics.uci.edu/ml/datasets/rice+leaf+diseases

[7] https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

[8] https://www.apsnet.org/edcenter/resources/ImageDatabase/Pages/default.aspx

extracting a set of informative features that effectively represent the patterns and characteristics associated with the disease. Hand-crafted features, designed based on domain knowledge, prove valuable in this regard. These features can include shape-based features (e.g., size, perimeter, circularity), texture-based features (e.g., Gabor filters, Haralick features), color-based features (e.g., color histograms, color moments, and spatial features (e.g., spatial distribution of disease symptoms). The careful selection and combination of these features provide a comprehensive representation of the disease, enabling accurate classification and diagnosis.
- Classification: Once the relevant features have been extracted, a classification model is trained to distinguish between healthy and diseased plants based on the extracted feature vectors. Standard ML models, such as support vector machines (SVMs) Sethy et al. (2020); Das et al. (2020), random forests (RFs) Mekha and Teeyasuksaet (2021), or multilayer perceptron (MLP) Kujawa and Niedbała (2021), can be effectively employed for this classification task.
- Evaluation: The performance of the hand-crafted feature-based plant disease detection model is rigorously evaluated using appropriate metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's ability to correctly identify healthy and diseased plants. Cross-validation or separate test datasets are commonly employed to evaluate the robustness and generalization capability of the model. This ensures that the model's performance is not influenced by the specific training data used and that it can generalize well to unseen data.

Region of Interest (ROI) Selection

In plant disease detection, not all parts of the plant exhibit visible symptoms associated with diseases. Focusing on specific ROIs, such as leaves, fruits, or flowers, enhances the efficiency and accuracy of the detection process Rodríguez et al. (2022). ROI selection effectively narrows down the analysis to the relevant areas where disease symptoms are more likely to occur, reducing computational burden and focusing processing power on the most informative regions. Moreover, ROI selection plays a crucial role in the feature extraction process, ensuring that the extracted features accurately represent the disease patterns. The selection of an appropriate ROI selection method depends on the specific requirements of the application and the available resources. ROI selection approaches can be broadly categorized into three main types: edge/thresholding, region-based, and learning-based Shrivastava and Tyagi (2015).

Edge- and threshold-based ROI selection techniques have proven to be effective in various plant disease recognition applications. Several edge-based segmentation methods, including the Canny edge detector Ahmed (2018), Sobel operator Yusoff et al. (2018), and Prewitt operator Muruganandam et al. (2022), have been successfully implemented in previous studies. These methods detect edges and boundaries of the plant parts, effectively separating them from the background. Additionally, thresholding-based techniques, such as Otsu thresholding Dutta et al. (2022), adaptive intensity-based thresholding Sengar et al. (2018), and entropy-based thresholding Ortega-Sánchez et al. (2022), are widely utilized for ROI selection. These techniques segment the image based on pixel intensity values, isolating the plant parts from the background. To further enhance ROI selection, hybrid approaches that combine region growing methods with local thresholding are often employed Deenan et al. (2020). These methods utilize the advantages of both techniques, effectively segmenting complex regions and isolating specific plant parts. However, it is crucial to note that improper selection of the threshold value in thresholding-based approaches can lead to incorrect ROI selection. Therefore, careful consideration of threshold selection is essential for accurate ROI determination.

Region-based ROI selection involves segmenting the image into distinct regions based on specific characteristics, such as color, texture, or pattern, and subsequently classifying each region as either diseased or healthy. One widely used algorithm for region-based ROI selection is the Watershed algorithm Tete and Kamlu (2017); Zhang et al. (2019c), inspired by the concept of flooding a topographical map. The algorithm begins by computing a gradient image from the input image, highlighting the edges and boundaries between regions. Next, the gradient image is transformed into a topographical map by treating the intensity values as height values. The algorithm then initiates a “flooding’ process from the catchment basins, defined as the local minima of the gradient image. This flooding process creates “watersheds” that separate the catchment basins, effectively segmenting the image into distinct regions Levner and Zhang (2007). Figure 4(b) illustrates the ROI selection results for two input leaf images using the Watershed algorithm.

Another region-based ROI selection algorithm is the Mean Shift algorithm Wu et al. (2014), which utilizes the concept of clustering to identify and segment regions of interest. This algorithm offers several advantages over other ROI selection methods. For instance, it exhibits robustness to noise and can effectively handle images with complex structures and shapes. However, it can be computationally expensive, especially for large and high-resolution images,

In several studies, learning-based ROI selection has been employed for segmenting diseased areas and has been discovered to be more effective and appropriate compared to edge-based ROI selection approaches. One approach utilizes fuzzy c-means clustering, which effectively segments diseased areas based on their distinct characteristics Kaur et al. (2019). Super-pixel clustering techniques, such as pyramid of HOG combined with k-means clustering, have also been employed to assist in disease spot segmentation Zhang et al. (2018); Pavel et al. (2019). These methods effectively group pixels into super-pixels based on their similarity, facilitating more accurate segmentation of diseased regions. For efficient lesion segmentation, researchers have explored various methods, including the GrabCut algorithm Qi et al. (2022); Li et al. (2020b) and weighted lesion segmentation schemes Sharif et al. (2018). The GrabCut algorithm is an interactive segmentation method that utilizes user input to guide the segmentation process, while weighted lesion segmentation schemes assign weights to different pixels based on their relevance to the lesion area, improving segmentation accuracy. Another approach to ROI selection is the sliding window method, which is simple and effective for identifying objects of interest in an image Dang et al. (2020b, a). This method involves sliding a window of a fixed size across the image and extracting features from the pixels within the window. The extracted features are then used to classify the window as either containing an object of interest or not. These learning-based ROI selection approaches have demonstrated promising results compared to traditional techniques such as Otsu thresholding, expectation maximization (EM), active contour segmentation, and saliency segmentation. Additionally, genetic algorithms have recently gained attention for segmentation in plant disease detection studies Arya et al. (2018); Khan et al. (2019). Genetic algorithms are optimization algorithms that mimic the process of natural selection to identify the optimal set of segmentation parameters, leading to more accurate ROI selection.

Feature Extraction

Features are crucial for object recognition and classification, as they capture and represent relevant and distinguishing characteristics that allow for the discrimination between healthy and diseased plant regions. In plant disease detection, feature extraction plays a pivotal role in constructing the disease detection model. This process involves extracting attributes such as color, texture, and shape from the spotted/infected area of the plant image. Feature extraction can be broadly categorized into two main types:

- Hand-crafted features: hand-crafted features are manually designed features that are engineered based on domain knowledge and a deep understanding of the specific problem at hand. These features are typically derived from well-established image processing techniques, such as texture analysis, color-based features, or shape descriptors Patil and Kumar (2017). Color features are employed to capture the color characteristics of the diseased areas, such as hue, saturation, and luminance. These features can be effectively represented using various methods, such as histograms, moments, and color spaces Owomugisha and Mwebaze (2016). Texture features, such as contrast, variance, and entropy, describe the texture properties of the diseased areas and can be extracted using techniques like Gray-Level Co-occurrence Matrix (GLCM) Haralick et al. (1973), Gabor filters Mehrotra et al. (1992), and Local Binary Patterns (LBP) Ojala et al. (1994). Shape features, such as area, eccentricity, and roundness, capture the geometrical properties of the diseased areas and can be extracted using shape-based methods like Fourier descriptors Persoon and Fu (1977) and Hu moments Azim et al. (2021). The selection of appropriate color, texture, and shape features is crucial for designing an accurate and efficient plant disease detection system. The choice of features should be carefully tailored to the specific plant disease being detected and the characteristics of the plant images being used Madiwalar and Wyawahare (2017).
- Deep features: with the advent of DL, CNNs have emerged as a powerful tool for automatic feature extraction in various image-based tasks, including plant disease detection. CNNs excel at learning hierarchical representations from raw image data, automatically extracting relevant features at different levels of abstraction, eliminating the need for manual feature engineering Li et al. (2020a); Sethy et al. (2020). These features can be extracted from intermediate layers of the network, known as bottleneck features, or from the output of fully connected layers. By leveraging their ability to learn hierarchical representations of visual information, CNNs capture both low-level and high-level visual patterns, enabling more com-

prehensive and discriminative representations of plant diseases. This approach has proven to be effective in various plant disease identification tasks. For instance, a study by Li et al. (2020a) proposed two alternative models that employed shallow CNNs with kernel SVM and RF, demonstrating that the feature extractor-based approach outperformed other pretrained deep models while requiring fewer parameters. CNNs are also commonly utilized as backbones in object detection pipelines to extract features from images, which are subsequently employed for object classification Zou et al. (2023); Saleem et al. (2020). Figure 7 demonstrates a sample rice leaf disease detection system based on an SVM model that was trained on extracted deep features from different pretrained CNN models.

Hand-crafted features have been prevalent in early plant disease detection works, offering interpretability and explainability as they can be directly linked to specific visual characteristics of the diseases. However, designing effective hand-crafted features demands expertise and can be time-consuming. Moreover, hand-crafted features may not capture all relevant information in complex and diverse plant disease images, limiting their discriminative power. Deep features, on the other hand, have the advantage of being automatically learned from data, eliminating the need for manual feature engineering. However, they can be less interpretable compared to hand-crafted features, as the learned representations are derived from complex neural network architectures Minh et al. (2022). In terms of classification performance, while hand-crafted features have been widely used in the past, they have been largely superseded by DL methods, which have demonstrated superior performance Jackulin and Murugavalli (2022). The choice between these approaches depends on the specific requirements of the plant disease detection task, the availability of labeled data, and the trade-off between interpretability and discriminative power.

Disease Classification

In conventional plant disease detection methods, disease classification involves assigning a specific disease class to an input plant sample based on its extracted features. Once relevant features have been extracted from plant images, various classification

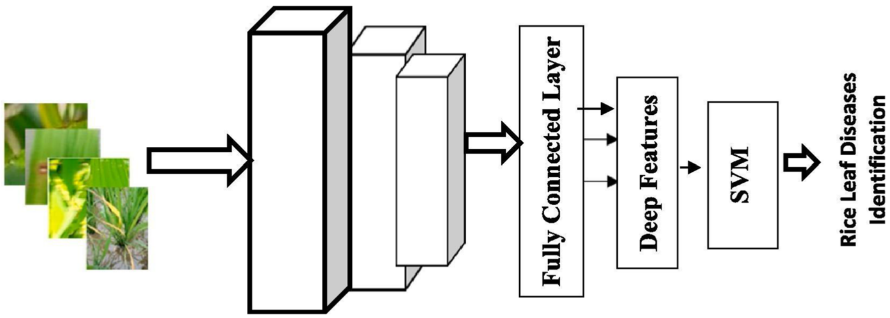


Fig. 7 A sample rice leaf disease detection framework by training SVM model with deep features (Sethy et al. (2020))

algorithms can be employed to categorize the samples into distinct disease classes Shruthi et al. (2019). The performance of these algorithms is heavily dependent on the outcomes of preceding processes. In general, traditional disease classification can be divided into two main approaches: supervised learning and ensemble-based learning techniques.

- Supervised learning utilizes a labeled training dataset to train a classification model, enabling it to learn the relationship between extracted features and corresponding disease labels Sujatha et al. (2021). Popular supervised learning algorithms, including SVMs Sahu and Pandey (2023), RFs Panigrahi et al. (2020), and K-nearest neighbors (KNN) Qin et al. (2016), can effectively classify plant samples into distinct disease classes. These algorithms make predictions based on patterns learned from the training data, ensuring accurate disease classification. In addition to these common algorithms, techniques such as logistic regression (LR), Naive Bayes (NB), and MLP can also be employed for disease classification in traditional plant disease detection. LR models the probability of a plant sample belonging to a specific disease class based on extracted features Das et al. (2020). NB assumes conditional independence of features given the disease class and calculates the probability of a sample belonging to a specific class Johannes et al. (2017); Qin et al. (2016). MLP can learn complex mappings between input features and disease classes, enabling accurate classification Kumari et al. (2019).
- Ensemble learning involves combining multiple classifiers to improve classification accuracy Shirahatti et al. (2018). Examples of ensemble methods include AdaBoost and gradient boosting. These methods leverage the strengths of individual classifiers and aggregate their predictions to achieve better performance. By combining diverse classifiers, ensemble methods can effectively handle complex and diverse plant disease patterns, resulting in improved disease classification accuracy. For instance, Shafi et al. (2021) extracted 6 GLCM features and 4 LBP features from yellow rust disease images. They then trained different boosting algorithms, including XGBoost, CatBoost, and LightGBM, using these extracted features. The experimental results showed that CatBoost reached the highest accuracy of 92.3% when using GLCM texture features. Ensemble methods offer a powerful approach for enhancing disease classification performance by leveraging the complementary strengths of multiple classifiers.

Table 4 provides an overview of various studies that have employed traditional plant disease detection. These studies utilize hand-crafted features such as color, shape, and texture, which are then used to train classification models. The table also highlights the emerging trend of extracting deep features. Notably, Sethy et al. (2020) obtained an outstanding classification accuracy of 98% by using a pre-trained CNN in conjunction with an SVM classifier on a dataset of 5932 rice images. Another successful approach involved the use of shallow CNNs, as demonstrated by Li et al. (2020a), who combined a shallow CNN with kernel SVM and RF classifiers, resulting in an accuracy of 94%. Other studies have explored various feature extraction techniques, including color, shape, and texture, along with different classifiers such as SVM, RF, and NB. Generally, studies that utilized multiple feature extraction techniques and classifiers demonstrated superior performance compared to those relying on a single feature.

Table 4 Comparison of plant disease detection based on hand-crafted features extraction approach

Plant	Disease	# images	Pre-processing	Features	Classifier	Performance	Reference
PlantVillage	38 classes	54,305	Enhancement, cropping, smoothing	Superpixel	Hybrid (RF & MCSVM	ACC 98.9%	Sahu and Pandey (2023)
Rice	Blight, blast	619	-	Color	SVM	ACC 94.7%	Shrivastava and Pradhan (2021)
	Tungro, blight, spot	5932	Resize	Pretrained CNN	SVM	ACC 98%	Sethy et al. (2020)
Wheat	Yellow rust	996	Resize	Texture	CatBoost	ACC 92.3%	Shafi et al. (2021)
Maize	9 classes	2000	-	Shallow CNN	Kernel SVM, RF	ACC 94% (Kernel SVM), 94% (RF)	Li et al. (2020a)
	Blight, rust and spot	3852	Grayscale, resize	Color, shape, texture	SVM, RF, NB	ACC 77.5% (SVM), ACC 79.2% (RF), ACC 77.4% (NB)	Panigrahi et al. (2020)
Grape	Blight, esca, rot	350	Histogram equalization, background subtraction	Color, shape, texture	SVM, KNN, (ABC optimization)	ACC 92% (SVM), ACC 89% (KNN)	Andrushia and Patricia (2020)
Tomato	8 classes	14,000	Resize, thresholding	Color, texture	LR, RF, SVM	ACC 67.3% (LR), ACC 70.05% (RF), ACC 87.6% (SVM)	Das et al. (2020)
	10 classes	3535	Color thresholding, median filtering	Color, SIFT	Multiclass SVM	ACC 85.1%	Hlaing and Zaw (2018)
Grape	4 classes	276	Grabcut	LBP	SVM	ACC 95%	Pantazi et al. (2019)
Cotton, tomato	4 classes	-	L*a*b* conversion, (clustering)	Cluster	ANN	ACC 92.5%	Kumari et al. (2019)

Table 4 continued

Plant	Disease	# images	Pre-processing	Features	Classifier	Performance	Reference
Self	6 classes	276	-	Region growing algorithm	BRBFNN SVM, GA	Partition coefficient 0.86 (BRBFNN), 0.83 (SVM), 0.81(GA)	Chouhan et al. (2018)
-		40	Median filtering, thresholding	Color, shape, texture	MLR	ACC 93.3%	Sun et al. (2018)
Wheat	Septoria, rust and tan spot	3500	Color constancy, leaf segmentation	Color, texture	NB, RF	AUC 0.82	Johannes et al. (2017)
Potato	Blight	300	Histogram analysis (L*, a* and b*), ROI segmentation	Color, texture	Multiclass SVM	ACC 95%	Islam et al. (2017)
Alfalfa	Leaf spot, rust	899	L*a*b* and HSV conversion, segmentation (clustering)	Color, shape, texture	SVM, KNN, NB	ACC 97.7% (SVM), ACC 80% (NB)	Qin et al. (2016)

Note: # images (number of images), ACC (accuracy), AUC (area under the ROC curve)

The most effective systems achieved accuracy ranging from 90% to 98%, which is commendable given the inherent challenges of plant disease detection.

In traditional plant disease recognition, the performance of the system is heavily influenced by various factors, each of which relies on expert judgment and meticulous decision-making Liakos et al. (2018). These factors include the selection of pre-processing and ROI selection techniques, the choice of color space, the determination of relevant features to extract, and the selection of the appropriate ML algorithm for classification Le et al. (2019); Das et al. (2020); Shrivastava and Pradhan (2021). Identifying the optimal combination of pre-processing, feature engineering, and ML model without extensive experimentation remains a challenging task. Consequently, developing an automatic plant disease recognition system using hand-crafted feature extraction often involves a laborious trial-and-error process. Furthermore, hand-crafted methods have demonstrated limited performance when confronted with slight variations in configurations, as they are specifically designed for controlled and constrained settings Sujatha et al. (2021); Wani et al. (2022). ROI selection techniques also pose challenges, particularly in the presence of complex backgrounds or when precise separation of diseased regions from healthy regions becomes difficult, leading to suboptimal outcomes Shruthi et al. (2019).

Deep Learning (DL) Approach

CNNs have revolutionized various CV tasks in recent years due to their ability to automatically extract meaningful features from image data. Unlike traditional ML methods that rely on hand-crafted features, DL models have demonstrated remarkable accuracy and generalization capabilities, often outperforming their predecessors Alzubaidi et al. (2021). This eliminates the need for extensive human intervention and allows DL models to automatically extract and analyze relevant features. A prime example of this success is the ImageNet challenge, where CNNs achieved a breakthrough in image classification accuracy Russakovsky et al. (2015). CNNs excel at identifying patterns and features in images by employing convolutional layers that apply filters to capture spatial relationships within the images. These extracted features are then combined and processed by subsequent layers to make predictions, leading to robust and accurate image classification.

CNNs have revolutionized various agricultural applications, making significant contributions to disease and pest recognition Johannes et al. (2017); Madiwalar and Wyawahare (2017), weed detection Yu et al. (2019), fruit and flower counting Rahim and Mineno (2020); Afonso et al. (2020), and fruit sorting and grading Nasiri et al. (2019). In particular, DL has transformed crop disease recognition since 2015 Bengio et al. (2021). The application of DL in agriculture holds immense potential for advancing the industry across several domains, including disease diagnosis, pest detection, quality management, marketing, automation, robotics, and handling large-scale datasets Liu and Wang (2021). Figure 8 illustrates the categorization of DL into distinct learning approaches, including classification, detection, and segmentation and other approaches, based on their respective architectures and underlying principles.

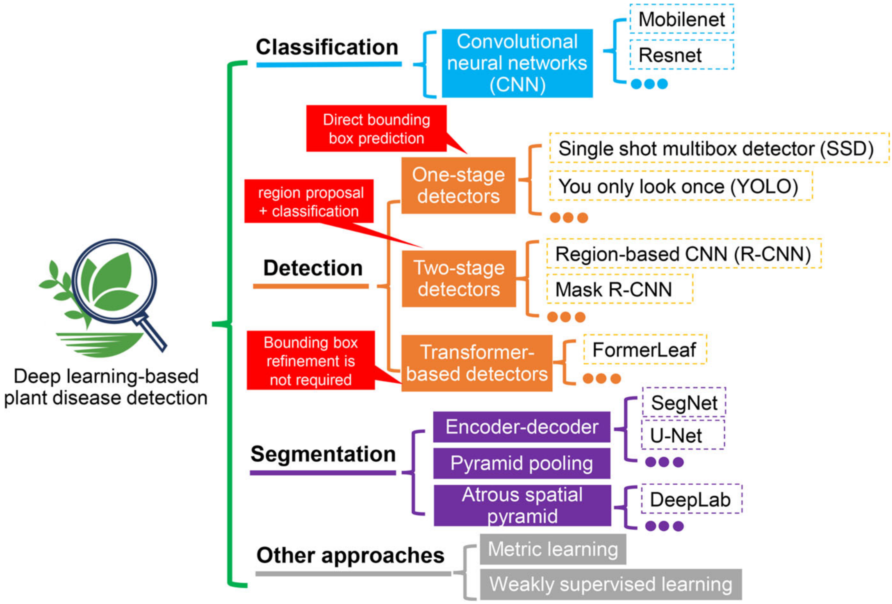


Fig. 8 Main DL-based approaches for plant disease detection

Plant Disease Classification

Identifying plant diseases in natural environments poses significant challenges due to the diverse variations in shape, texture, size, background, and lighting conditions Liakos et al. (2018). However, CNNs have revolutionized plant disease classification by harnessing their powerful feature extraction capabilities and have emerged as the dominant approach in this field. As displayed in Fig. 9, CNN-based plant disease classification networks typically consist of multiple layers designed to extract and process features from input plant images.

The architecture commonly starts with a series of convolutional layers, which apply filters to the input image to extract local patterns and features. These convolutional layers are often followed by activation functions, such as Rectified Linear Unit (ReLU),

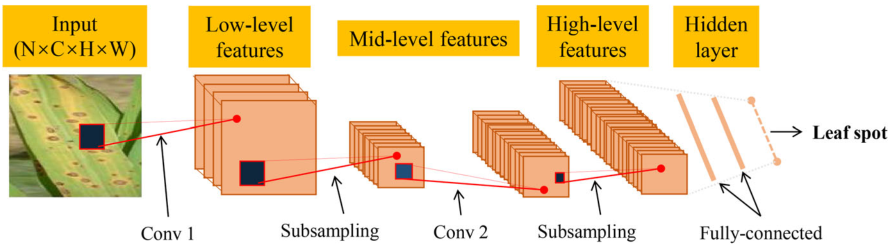


Fig. 9 A typical DL-based architecture for plant disease classification, **Note:** Conv (convolutional layer), C (number of channels), H (height), W (width))

to transform linearity into non-linearity. Pooling layers, such as max pooling, are then employed to reduce spatial dimensions and capture the most important features. The extracted features are then sent through fully connected layers, which perform high-level feature representation and classification. The final layer typically utilizes a softmax activation function to assign probabilities to different disease classes. To train the network, a large labeled dataset is used, and optimization techniques like backpropagation and gradient descent are employed to adjust the network's parameters and minimize the classification error Gu et al. (2018).

Once trained, the DL model can be deployed to classify new plant images by assigning them to the corresponding disease category. This facilitates automated and rapid disease diagnosis, enabling early intervention and empowering farmers to make informed decisions to mitigate the impact of plant diseases on crop yield. Several standard CNN architectures have gained widespread popularity for plant disease classification tasks, including MobileNet Bi et al. (2022); Sutaji and Yıldız (2022), VGG Coulibaly et al. (2019); Hernández and López (2020); Hang et al. (2019), GoogleNet Chen et al. (2020); Barbedo (2019), ResNet Shin et al. (2021), and DenseNet Kaya and Gürsoy (2023). These architectures are renowned for their deep and complex structures, enabling them to extract hierarchical representations of features from plant images. Typically, these architectures comprise multiple layers, including convolutional layers, pooling layers,

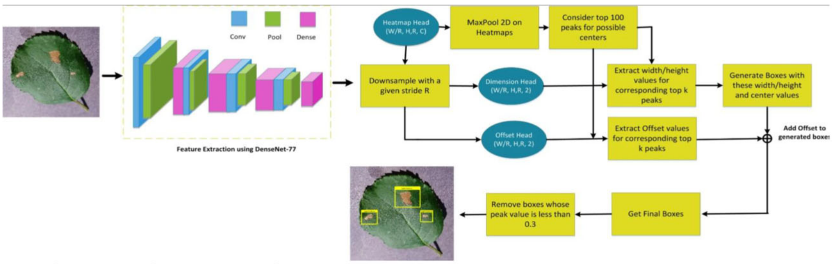
The limited availability of plant disease images often necessitates the use of transfer learning, where pre-trained models developed on large-scale image datasets like ImageNet are fine-tuned for plant disease classification Coulibaly et al. (2019); Chen et al. (2020). This approach harnesses the vast knowledge acquired from general image recognition tasks and adapts it to the specific goal of plant disease classification, even with limited training data. Attention mechanisms, a recent development in plant disease classification, selectively focus on crucial regions or features within an image, enhancing the network's performance and interpretability Minh et al. (2022). Furthermore, ensemble learning methods can be employed for plant disease classification by combining multiple individual classifiers using techniques such as majority voting, weighted voting, or stacking Sagi and Rokach (2018). Ensemble learning enhances the performance of plant disease classification frameworks by incorporating the collective knowledge of diverse classifiers. For instance, Turkoglu et al. (2022) evaluated the performance of six CNN models individually and as an ensemble model on the Turkey-Plant dataset. By utilizing an SVM classifier, the authors assessed various combinations of the models and achieved remarkable performance. Notably, the majority voting ensemble model yielded an accuracy of 97.56%, while the early fusion ensemble model achieved an accuracy of 96.83%. These results underscore the efficacy of ensemble classification methods in augmenting the performance of plant disease detection systems.

Plant Disease Detection

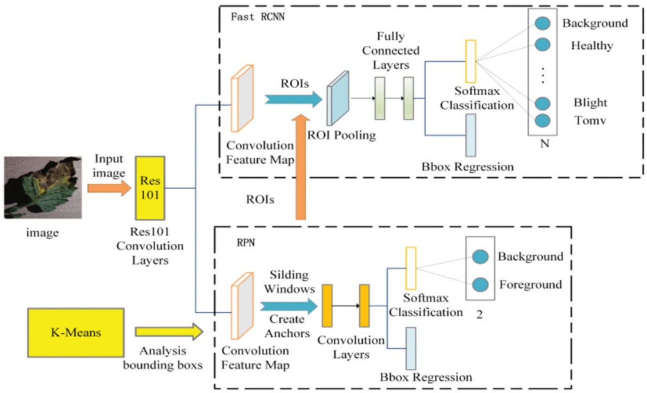
DL-based object detection has emerged as a powerful approach for addressing the task of plant disease detection. Unlike the disease classification approach, which only identify the presence or absence of diseases, DL-based object detection not only classifies diseases but also precisely localizes the affected regions within the images. This capability is particularly valuable for farmers and specialists as it provides a more detailed and actionable understanding of the extent of disease infestation.

The process of DL-based object detection for plant diseases typically begins with a large dataset of labeled images. Each image is annotated with bounding boxes that specify the location of the disease regions. These bounding boxes are associated with corresponding class labels indicating the type of plant disease present Kaustubh (2020). The neural network models used for object detection in plant disease detection tasks are usually based on architectures like region-based CNN (R-CNN) Seetharaman and Mahendran (2022), You Only Look Once (YOLO) Diwan et al. (2023), or Single Shot MultiBox Detector (SSD) Sun et al. (2021). These models consist of convolutional layers that learn to extract meaningful features from input images. These features are then passed through region proposal or detection layers that accurately identify and localize diseased regions. Figure 10(a) and (b) provide two different samples of plant disease detection based on CenterNet and Faster R-CNN, respectively.

During the training phase, the model iteratively updates its parameters by minimizing a loss function that quantifies the discrepancy between the predicted bounding boxes and class labels and the ground truth annotations. This process allows the



(i) Custom CenterNet for plant disease detection (Albattah et al. (2022)



(ii) Improved Faster-RCNN for grape leaf disease detection Xie et al. (2020)

Fig. 10 Two sample DL-based models for plant disease detection, **Note:** Conv (convolutional layer), C (number of channels), H (height), W (width)) model to learn the complex patterns and features associated with various plant diseases. Once trained, the model can be deployed to classify plant diseases in unseen images, providing valuable insights for early disease diagnosis and informed plant disease management strategies. DL-based object detection offers several advantages over traditional methods for plant disease detection, including higher detection rate, faster processing speeds, and the ability to detect multiple diseases simultaneously. As detailed in Table 5, DL-based object detection techniques for plant disease detection can be broadly categorized into four main groups: single-stage, two-stage, mask-based, and transformer-based approaches.

- Single-stage plant disease detection:
  YOLO and SSD are widely used models for single-stage plant disease detection. These models employ a single neural network, streamlining the detection process and enabling real-time or near-real-time performance Diwan et al. (2023). By utilizing advanced techniques such as anchor boxes and feature pyramids, these models can effectively locate and classify diseased regions within images, offering a practical solution for rapid and accurate plant disease detection and monitoring. For instance, Chen et al. (2022b) customized the original YOLOv5 model to achieve precise detection of plant diseases, even in challenging outdoor environments. Their approach involved incorporating an InvolutionBottleneck module, which efficiently reduced the number of parameters and computations while capturing long-range information. Additionally, an SE module was added to enhance

Table 5 Comparison of advantages and disadvantages of each DL-based detection sub-methods

Detection type	Sample model	Advantages	Disadvantages
Single-stage	YOLO Chen et al. (2022b), SSD Saleem et al. (2020)	• Faster processing speed due to single pass • Good performance on small objects	• Lower accuracy than two-stage methods • Struggle with occlusion and overlapping objects
Two-stage	Faster R-CNN Bari et al. (2021); Zhang et al. (2020), R-FCN Dai et al. (2016)	• Higher accuracy due to two-stage pipeline • Better at detecting occluded/overlapping objects	• Slower processing speed than single-stage methods • May struggle with small objects
Mask-based	Mask R-CNN Afzaal et al. (2021)	• Can detect object boundaries • Can generate pixel-level segmentation	• Slower processing speed than two-stage methods • Resource-intensive due to generating masks
Transformer-based	DETR Yu et al. (2023)	• No need for anchor boxes • Global context improves accuracy	• Slower processing speed than other methods • May struggle with small objects

the model's sensitivity towards channel features. The authors also replaced the original YOLOv5 model's loss function with an enhanced intersection over union (EIoU) loss. The model was evaluated using sample images from a rubber tree disease database and achieved a mean average precision (mAP) of 70%, outperforming the original YOLOv5 network by 5.4%. In another study, Saleem et al. (2020) compared the SSD model with various models using the annotated PlantVillage dataset to identify the most suitable model for classifying and localizing plant leaf diseases. The experimental results demonstrated that the model using the Adam optimizer achieved an mAP of 73.07%, surpassing the performance of other models.

- Two-stage plant disease detection:
  Two-stage object detection has emerged as a prevalent technique for plant disease detection, leveraging on the strengths of specialized stages to achieve accurate localization and classification of diseased regions in plant images Du et al. (2020). This approach employs a first stage dedicated to generating region proposals, followed by a refinement stage that performs the final classification. Representative two-stage detection models include Faster R-CNN and region-based fully convolutional network (R-FCN) Dai et al. (2016). For instance, Bari et al. (2021) successfully implemented a Faster R-CNN algorithm equipped with an enhanced RPN architecture for rice leaf disease detection. The model effectively diagnosed three distinctive rice leaf diseases and identified healthy rice leaves in real-time, achieving an average accuracy exceeding 98%. In a contrasting approach, Xie et al. (2020) presented a real-time grape leaf disease detection method aimed at enhancing grape yield through early disease detection and diagnosis. The proposed method seamlessly integrates the Faster R-CNN detection algorithm with the Inception-v1 module, Inception-ResNet-v2 module, and SE-blocks to extract diseased spot features and precisely localize common grape leaf diseases while maintaining a satisfactory detection speed. Notably, the detection mAP reached 81.1% on the grape leaf disease dataset, accompanied by a real-time detection speed of 15 frames per second (FPS).
- Mask-based plant disease detection: Mask-based object detection for plant disease is a sophisticated technique that surpasses the limitations of identifying diseased regions using bounding boxes by providing pixel-level segmentation masks to precisely delineate the affected areas. This approach enables a more detailed and accurate assessment of the spatial extent of plant diseases within images Sun et al. (2021). It typically employs architectures such as Mask R-CNN or U-Net, which combine object detection capabilities with semantic segmentation. For instance, Afzaal et al. (2021) presented a Mask R-CNN-based framework that utilized a ResNet backbone and introduced a systematic data augmentation technique, allowing for effective segmentation of strawberry diseases even under challenging background conditions. Their model achieved an mAP of 82.43%, demonstrating accurate identification and segmentation of strawberry diseases. In another study, Su et al. (2020) collected wheat spike images and corresponding fusarium head blight infection levels to train a Mask-RCNN model. The study demonstrated reliable detection of both diseased areas and wheat spikes, with detection rates of 98.81% and 77.76%, respectively. The Mask-RCNN algorithm exhibited robust

capability in detecting targets that were occluded by wheat awns or located at the image borders.

- Transformer-based plant disease detection: Recent research has demonstrated that the transformer model, originally developed for natural language processing (NLP) tasks but successfully adapted for CV tasks, including object detection, has achieved state-of-the-art performance compared to DL-based approaches Dang et al. (2022). In this approach, the input image is initially processed by a pre-trained CNN to extract image features, which are then fed into the transformer model for plant disease detection. For instance, Thai et al. (2023) introduced a transformer-based model called FormerLeaf specifically designed for detecting leaf diseases and proposed two optimization methods to enhance its performance. The first method, least important attention pruning, selectively identifies and removes the most redundant attention heads in each layer of the transformer model. By applying this pruning technique, the model size can be reduced by up to 28%, leading to an improvement in accuracy of approximately 3%. The second method, sparse matrix-matrix multiplication, significantly reduces the model's complexity and training time by 10% while maintaining comparable performance. Evaluation results obtained from the Cassava leaf disease dataset demonstrated the superiority of the model over other object detection models in most scenarios.

Plant Disease Segmentation

The segmentation network plays a pivotal role in the identification and differentiation of plant diseases Minaee et al. (2021). By accurately segmenting lesion areas, the segmentation approach facilitates the precise identification of lesion location, size, and geometric properties, including length, width, surface area, contour, and center. This enables a more detailed and comprehensive understanding of the disease progression and severity. Segmentation models can be categorized into distinct types based on their underlying architecture and approach, as summarized in Table 6.

- Encoder-decoder network: it is a versatile architecture widely used for plant disease segmentation. It comprises two main pathways: the encoder pathway and the corresponding decoder pathway. The encoder pathway progressively downsamples the input image to extract high-level features. These extracted features are then fed into the decoder pathway, which upsamples them back to the original image size, generating a dense segmentation map. Several standard encoder-decoder structures have been effectively implemented for plant disease segmentation, including U-Net Zhang and Zhang (2023); Putra et al. (2022), SegNet Douarre et al. (2019); Kerkech et al. (2020), FCN Ngugi et al. (2021), and LinkNet Deng et al. (2022); Arvind et al. (2021). For instance, Zhang and Zhang (2023) proposed incorporating a residual block (Resblock) and a residual path (Respath) into the U-Net architecture to address the challenges of gradient disappearance and explosion, which can hinder the training process. The Resblock effectively mitigates these issues, while the Respath replaces traditional skip connections and enhances the information flow between the contraction path and the expansion path of the U-Net. This approach improves the network's capability to handle complex leaf images and

Table 6 Comparison of architectures for plant disease segmentation

Module	**Model**	Reference	**Strengths**	**Weaknesses**
Encoder-decoder	U-Net	Zhang and Zhang (2023); Putra et al. (2022)	• Well-suited for limited data scenarios • Fast inference	Struggle with capturing fine details
	SegNet	Kerkech et al. (2020); Douarre et al. (2019)	• Efficient architecture • Effective in handling limited training data	Limited capability in capturing complex object
	LinkNet	Deng et al. (2022); Arvind et al. (2021)	• Efficient architecture • Fast training and inference	Struggle with capturing fine details
	FCN	Polder et al. (2019); Ngugi et al. (2021)	• Efficient end-to-end training • Fast inference	Produce coarse segmentation
Pyramid Pooling	PSPNet	Liu et al. (2022); Pan et al. (2021)	• Incorporates multi-scale contextual information • Captures fine details	• Higher memory usage • Slower training
Atrous Spatial Pyramid	DeepLab	Zhu et al. (2023); Wang et al. (2021a)	Uses atrous convolutions to control field-of-view	Sensitive to parameter tuning

enhances segmentation accuracy and efficiency. In another study, Kerkech et al. (2020) employed a SegNet model to segment Mildew disease in vineyards into four classes: shadow, ground, healthy, and symptomatic. As illustrated in Fig. 11, the authors fused visible and infrared segmented images to create a comprehensive disease map. The model demonstrated an impressive detection rate of 87% at the leaf level and over 92% at the grapevine level, highlighting its potential for decision support systems in vineyard disease detection.

- Pyramid pooling network (PPNs): PPNs are a class of architectures specifically designed to capture multi-scale contextual information for accurate segmentation. These architectures employ a pyramid pooling module that aggregates features at different scales, enabling the network to capture both fine-grained details and global context Yu et al. (2018). A prominent example of a PPN is the pyramid scene parsing network (PSPNet), which utilizes pyramid pooling as a key component to extract multi-scale contextual features for semantic segmentation tasks. For instance, Pan et al. (2021) successfully implemented the PSPNet model to segment healthy wheat, yellow rust wheat, and bare soil in small-scale UAV images. The study demonstrated that the PSPNet model achieved an impressive recognition accuracy of 98%.
- Atrous spatial pyramid networks (ASPNs): ASPNs employ atrous (dilated) convolutions to regulate the receptive field size and capture contextual information at multiple scales, enhancing their ability to segment complex plant images Ma et al. (2023). Atrous convolutions introduce gaps within the filters, allowing them to sample input signals at varying spacing rates. By adjusting the dilation rate, ASPNs can control the effective receptive field without significantly increasing computational overhead. DeepLab Chen et al. (2017), a widely used semantic segmentation model, utilizes atrous convolutions and atrous spatial pyramid pooling (ASPP) modules to refine spatial context and segmentation accuracy. For instance, Zhu et al. (2023) introduced a novel two-stage DeepLabv3+ architecture with adaptive loss for effectively segmenting apple leaf disease images with intricate backgrounds. To enhance the model's performance, the authors fine-tuned the dilation rates of atrous convolutions within the ASPP module, enabling better capture of smaller diseased regions. Additionally, they incorporated a channel attention

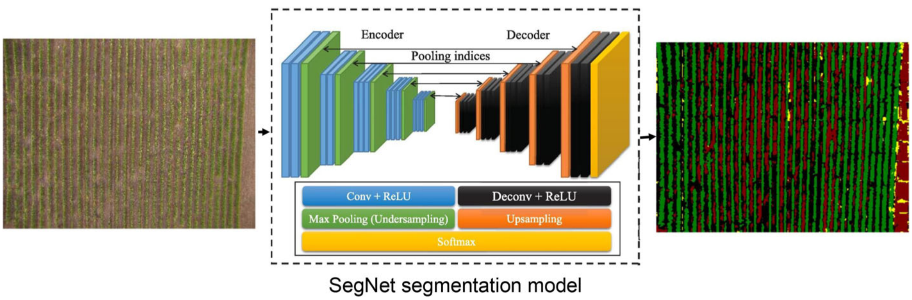


Fig. 11 Vineyard disease segmentation framework using a SegNet structure by Kerkech et al. (2020). The color code of the outputs: Green: healthy, Yellow: visible symptom, Orange: infrared symptom, Red: symptom intersection, Black: shadow, Brown: soil

block to emphasize significant spot disease information while suppressing less important background details. The experimental results demonstrated the efficacy of the proposed approach, achieving state-of-the-art intersection over union (IoU) scores of 98.7% for leaf segmentation and 86.56% for spot extraction.

Other Learning Techniques

Weakly Supervised Learning

Weakly supervised learning has emerged as a promising approach to address the limitations of traditional supervised learning methods in plant disease recognition. Unlike traditional methods that rely on pixel-level labeling, weakly supervised learning utilizes less stringent image-level annotations or weak labels, such as disease categories without precise lesion locations Zhou (2018). This approach significantly reduces the labeling burden, making it a more time-efficient and cost-effective solution. By effectively exploiting weak annotations, weakly supervised learning models can accurately classify and localize plant diseases, enabling timely and effective intervention strategies.

Weakly supervised learning techniques often leverage attention mechanisms, which direct the model's focus towards informative regions within an image that are likely to harbor signs of disease. Employing techniques like attention maps or saliency maps, these methods identify the most relevant regions for disease recognition Adke et al. (2022); Zhou et al. (2023). By guiding the model to prioritize these informative areas, weakly supervised learning algorithms can effectively localize and classify diseases without requiring precise pixel-level annotations Chen et al. (2022a). The potential of weakly supervised models for disease spot segmentation has been explored by Zhou et al. (2023). Their work introduced two approaches: ResNet-CAM, which combined Grad-CAM with ResNet-50, and weakly supervised leaf spot segmentation using a few-shot pretrained U-Net classifier (Fig. 12). Both models were trained using image-level annotations (healthy versus diseased), significantly reducing the need for time-consuming and expensive pixel-level annotations. Experimental results demonstrated that the weakly supervised approach outperformed the fully supervised DeepLab model when processing the additional testing dataset, achieving an IoU of 0.511 compared to 0.458 for DeepLab. This research highlights the promise of weakly supervised models for reducing annotation efforts while maintaining satisfactory segmentation performance

Despite the advantages of weakly supervised learning for plant disease recognition, such as reduced annotation effort and scalability, it also presents certain challenges. The lack of precise pixel-level annotations may lead to lower localization accuracy and difficulties in differentiating between similar disease patterns. Moreover, model interpretability and the ability to handle unseen or novel diseases remain open areas of research Zhou (2018).

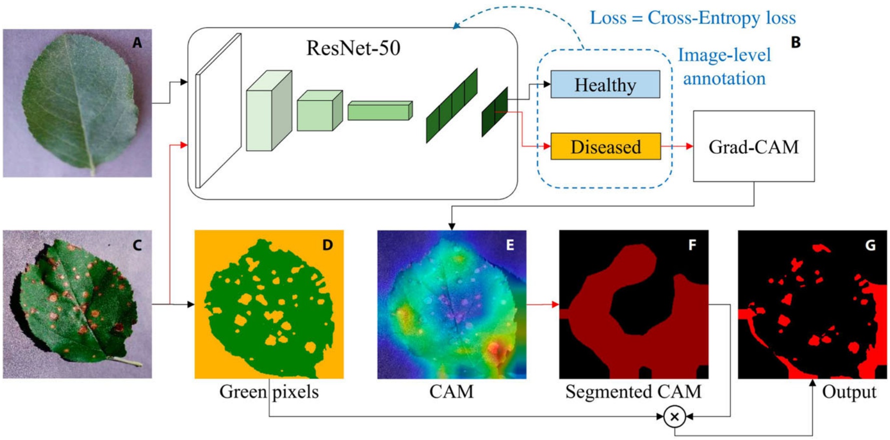


Fig. 12 A sample weakly supervised learning based on ResNet model and gradient-weighted class activation mapping (Grad-CAM) by Zhou et al. (2023), **Note:** CAM (class activation mapping)

Metric Learning

Metric learning has emerged as a promising technique for plant disease detection due to its ability to effectively discriminate and classify healthy and diseased plants based on learned similarity measures Janarthan et al. (2020). Metric learning algorithms strive to enhance disease detection performance by learning a suitable distance metric or similarity function that improves the distinction between different disease classes. A key advantage of metric learning in plant disease detection lies in its ability to capture intricate relationships and patterns within the data. Metric learning algorithms typically operate on pairs or triplets of samples. In the context of plant disease detection, pairs of images can be compared to determine their similarity or dissimilarity based on the learned metric. The primary objective of metric learning algorithms is to minimize the distance between similar pairs (such as images of the same disease) while concurrently maximizing the distance between dissimilar pairs (such as images of different diseases or healthy plants). This process effectively generates a feature space where similar samples are grouped together, enabling accurate disease classification.

Several approaches exist for metric learning in plant disease detection, including Siamese networks and Triplet networks. Siamese networks employ twin neural networks that share weights and are trained to embed similar images close together in the feature space. For instance, Janarthan et al. (2020) proposed a lightweight and robust deep Siamese network-based framework specifically tailored for citrus disease detection using sparse data. The proposed framework incorporated a patch-based classification network, an embedding module, a cluster prototype module, and a simple neural network classifier. This approach has a remarkable advantage in its ability to effectively learn with limited resources while maintaining high accuracy. This enhanced practical applicability makes the architecture particularly suitable for resource-constrained devices like mobile phones.

In contrast to Siamese networks, triplet networks learn embeddings such that the distance between an anchor image and a positive image (belonging to the same disease class) is minimized, while the distance between the anchor image and a negative image (from a different disease class or a healthy plant) is maximized. This approach forces the network to learn discriminative features that can effectively differentiate between different disease classes. In a notable example, You et al. (2022) proposed a practical and effective scheme for strawberry disease detection, including the identification of unknown diseases. Their approach utilizes deep metric learning-based classifiers, including the ResNet-50 model with margin triplet and cross-entropy losses. When evaluated using real-field data, the proposed scheme achieved an impressive mAP of 93.7% for accurately identifying known categories of strawberry diseases. Furthermore, the scheme demonstrated promising results for detecting disease-like symptoms caused by both known and unknown diseases or disorders in various plant species. This highlights the potential of metric learning for recognizing disease-like symptoms across a wide range of plant species and disease types

The effectiveness of metric learning for plant disease detection hinges on the availability of a comprehensive and representative dataset. A sufficient number of samples representing various diseases, including different stages and severities, should be included to ensure the model's ability to generalize effectively. Additionally, employing careful data pre-processing and augmentation techniques can further enhance the model's performance and robustness Li and Tian (2018).

Tables 7, 8, and 9 provide an overview of recent DL-based plant disease identification research. The tables summarize studies published between 2019 and 2023, highlighting the advancements in this field. Several trends and approaches are evident from these studies. Most studies utilize RGB images for disease identification, with the PlantVillage dataset being a popular choice. Various DL models, such as DenseNet, Faster R-CNN, and EfficientNet, are employed for classification and detection tasks. Data augmentation techniques and ensemble learning methods are commonly used to enhance model performance. Additionally, some studies explore novel techniques, such as attention optimization, transfer learning, and metric learning, to improve disease recognition accuracy. These tables showcase the progress made in DL-based plant disease recognition and serve as a valuable resource for researchers and practitioners in the field. However, it is important to note that the summarized information is limited to the tables and does not provide in-depth details about the methodologies, datasets, and evaluation protocols used in each study. For a comprehensive understanding of the research approaches and findings, it is recommended to refer to the original references.

Post-Processing

Following the training of classification models, additional post-processing steps, such as explainable artificial intelligence (XAI) can be employed to refine the model's predictions and extract more meaningful information. XAI for plant diseases involves the use of ML models that not only accurately classify plant diseases from images but also provide explanations or visualizations of the classification process. This capability is particularly valuable in plant disease detection as it enables farmers and specialists

Table 7 Comparison of plant disease recognition based on DL approach

Task	Plant	Disease (# images)	Sensor	Model	Performance	Novelty	Reference
C	Plant Village	38 classes	RGB (54,305)	DenseNet121	ACC 98.2%	Image fusion, multi-headed DenseNet-based architecture	Kaya and Gürsoy (2023)
				AgriDet framework	ACC 96%	End-to-end disease identification framework, transfer learning, disease severity categorization	Pal and Kumar (2023)
				New model (transformer)	**ACC 99.9%** ACC 77.5%	Soft split token embedding, depth-wise convolution transformer	Yu et al. (2023)
				Ensemble model	ACC 99.1%	Ensemble model of MobileNetV2 and Xception	Sutaji and Yıldız (2022)
				EfficientNet	ACC 99.97% PRE 99.3%	Augmentation	Atila et al. (2021)
				GoogLeNet	ACC 99.3%	Activation visualization	Chen et al. (2020)
				VGG16	ACC 96%	Bayesian learning schemes, uncertainty quantification	Hernández and López (2020)
				New model (9-layer)	ACC 96.4%	Augmentation, 9-layer CNN model	Geetharamani and Pandian (2019)
				Pruned MobileNet	ACC 98.3%	Uses depth-wise separable convolutions	Kamal et al. (2019)
	Apple	Blotch & rust	RGB (2004)	MobileNet	ACC 73.5%	-	Bi et al. (2022)
		Rust, scab, blotch spot	RGB (1821)	InceptionV3 & HOG	ACC 99.8%	Augmentation, feature fusion	Fan et al. (2022)
		10 classes	RGB (6108)	Customized VGG16	ACC 91.7%	VGG16 architecture optimization	Hang et al. (2019)

Table 7 continued

Task	Plant	Disease (# images)	Sensor	Model	Performance	Novelty	Reference
	Tomato	10 classes	RGB (16,012)	DenseNet121	ACC 97%	Synthetic images (C-GAN)	Abbas et al. (2021)
				Compressed VGG16	ACC 98.4%	Augmentation, new CNN model (compressing VGG16)	Agarwal et al. (2020)
				Three-channel CNN	ACC 91.1%	Improves the performance by using high-level color features	Zhang et al. (2019b)
	Cassava	5 classes	RGB (21,397)	New model (ViT-based)	F1 96.8%	Pruning algorithm to optimize attention heads, sparse matrix-matrix multiplication to reduce training time	Thai et al. (2023)
	Self	Lesions & spots	RGB (46,409)	GoogLeNet	ACC 78.3%	Augmentation, a large plant disease dataset	Barbedo (2019)
		15 classes	RGB (4447)	Ensemble model	ACC 97.6%	Ensemble learning & combine six CNN models	Turkoglu et al. (2022)

Note: # images (number of images), ACC (accuracy), C (classification), PRE (precision)

Table 8 Comparison of plant disease identification based on DL approach (continue)

Task	Plant	Disease	Sensor (# images)	Model	Performance	Novelty	Reference
C	Tea	Blight, scab	RGB (144)	Customized CIFAR10-quick	ACC 92.5%	Augmentation, multiscale feature extraction, depthwise separable convolution	Hu et al. (2019)
		7 classes	RGB (3810)	New model (5-layer)	ACC 90.1%	Augmentation, 5-layer CNN model	Chen et al. (2019)
	Radish	Fusarium wilt	RGB (2814) NIR (1997)	New model (5-layer)	ACC 96.4%	Superpixel segmentation, NVDI-based disease detection	Dang et al. (2020b, a)
	Millet	7 classes	RGB (124)	VGG16	ACC 95%	Augmentation, transfer learning	Coulibaly et al. (2019)
	Wheat	Yellow rust	Hyper spectral (15,000)	Inception-Resnet	ACC 85%	The model was trained on spatial and spectral features	Lin et al. (2019)
	Straw-berry	Mildew	RGB (11,600)	ResNet-50	PRE 98.4%	Augmentation & comparison of 6 CNN models	Shin et al. (2021)
	Mango	Fungal	RGB (2200)	New model (6 layers)	ACC 97.1%	Proposed a lightweight model inspired by the AlexNet	Singh et al. (2019)
	Rice	Blast	RGB (5808)	New model (7 layer)	ACC 95.8%	Augmentation, lightweight model, t-SNE assessment	Liang et al. (2019b)
	Cucum-ber	6 classes	RGB (30,000)	New model (13 layers)	ACC 94.6%	Dilated convolution kernel & multi-scale features extraction	Zhang et al. (2019d)
	AICha-llenger	45 classes	RGB (25,000)	New model	ACC 98%	Augmentation, a new model containing a residual structure and shuffle units, disease severity estimation	Liang et al. (2019a)

Table 8 continued

Task	Plant	Disease	Sensor (# images)	Model	Performance	Novelty	Reference
D	Plant Village	38 classes	RGB (54,305)	Custom CenterNet (DenseNet-77)	PRE 99.5%	DenseNet-77 is used for feature extraction, robust to the presence of several artifacts	Albattah et al. (2022)
				SSD (Inception-v2)	mAP 73.1%	Meta-architectures	Saleem et al. (2020)
	Rubber	Mildew & anthracnose	RGB (2375)	YOLOv5	PRE 86.5%	InvolutionBottleneck, SE, EIOU	Chen et al. (2022b)
	Grape	BBlack rot, esca, blight, mites	RGB (62,286)	Faster R-CNN	mAP 81.1%	Augmentation, Inception-v1 module, Inception-ResNet-v2 module and SE-blocks is introduced to Faster R-CNN	Xie et al. (2020)
	Tomato	9 class	RGB (4,178)	Faster R-CNN	mAP 98.5%	Anchoring improvement (K-means clustering)	Zhang et al. (2020)
	Sugar beet	Leaf spot	RGB (155)	Faster R-CNN	ACC 95.5%	Customize the architecture of Faster R-CNN	Ozguven and Adem (2019)
	Apple	5 classes	RGB (2029)	SSD (Inception module, Rainbow concatenation)	mAP 78.8%, FPS 23.1	Apple leaf disease dataset, improved SSD	Jiang et al. (2019)
	Banana	5 classes	RGB (12,600)	Faster R-CNN	mAP 0.96	Transfer learning	Selvaraj et al. (2019)

Note: # images (number of images), ACC (accuracy), C (classification), D (detection), mAP (mean average precision), PRE (precision)

Table 9 Comparison of plant disease identification based on DL approach (continue)

Task	Plant	Disease	Sensor (# images)	Model	Performance	Novelty	Reference
S	Maize	Blight	RGB (172)	New model	ACC 91%	End-to-end training approach, simultaneous segmentation of individual leaf instances and corresponding diseased region	Garg et al. (2021)
		Lesion	RGB (79,919)	CNN & CRF	ACC 99%	Data crowdsourcing	Wiesner-Hanks et al. (2019)
	Grape	Healthy & systematic	RGB (105,515), IR (98,895)	SegNet (VGG16)	94.4% (RGB) 89.1% (IR)	Semi-automatic labeling, augmentation, fusion of both RGB and IR	Kerkech et al. (2020)
	Potato	Virus Y	Hyper spectral (35,200)	FCN	PRE 0.78%, REC 0.88%	Real field hyperspectral-based approach a new hyperspectral imaging setup	Polder et al. (2019)
	Apple	Scab	IR (550)	SegNet	F1 0.64	Automatic annotated data generation, IR data collection	Douarre et al. (2019)
H	Plant Village	38 classes	RGB (54,305)	PSPnet & EfficientNet	IOU 61.4%	General DL-based disease identification, hybrid system	Mzoughi and Yahiaoui (2023)
				YOLOv5s	mAP 98%	Metric learning, image retrieval system	Peng and Wang (2022)
	Citrus	Black spot, canker, Huanglongbing	RGB (598)	Faster RCNN	PRE 94.6% REC 92.5%	Data pre-processing, a two-stage disease detection and classification model	Syed-Ab-Rahman et al. (2022)
	Cotton	Spot	RGB (1649)	DenseNet (SSO)	ACC 95.1%	Small-sample classification, SSO, metric learning	Liang (2021)
	Self	58 classes	RGB (79,265)	Hybrid model (detection + classification)	mAP 0.91%, ACC 93%	Augmentation, PlantDisease dataset (classification & detection)	Arsenovic et al. (2019)

Note: # images (number of images), ACC (accuracy), IOU (intersection over union), mAP (mean average precision), PRE (precision), REC (recall), H (Hybrid approach), S (segmentation) to better understand the underlying causes of diseases, such as environmental factors or genetic traits. Various techniques can be employed to achieve explainable classification, including feature importance analysis Carletti et al. (2019) and saliency maps Wei et al. (2022). For instance, Nagasubramanian et al. (2019) proposed a 3D deep CNN model that directly utilizes hyperspectral data for plant disease identification. The model achieved a remarkable classification accuracy of 95.73% and an infected class F1 score of 0.87 when detecting charcoal rot disease in soybean crops. The study further implemented a saliency map technique to visualize the most sensitive pixel regions, revealing that the model relied on wavelengths in the near-infrared (NIR) region for classification. The insights provided by the explained predictions generated by the model offer valuable physiological understanding and can have practical applications in precision agriculture and automated phenotyping platforms.

Evaluation Metrics

Table 10 presents a comprehensive overview of common evaluation metrics for plant disease classification, detection, and segmentation. In the classification task, metrics such as accuracy, precision, recall, and F1-score are employed to evaluate the correctness of classification predictions and the balance between true positives, false positives, and false negatives. For detection, metrics like IoU, mean average precision (AP), and average precision (mAP) are utilized to assess the accuracy of bounding box predictions and evaluate the model's performance across different confidence thresholds. In segmentation, pixel accuracy (PA) is used to measure the correctness of classified pixels, while the Dice coefficient (DSC) quantifies the similarity between predicted and ground truth segmentation masks. These evaluation metrics provide quantitative measures to assess the performance of models in plant disease analysis, enabling comparisons between different approaches and facilitating the selection of the most effective ones.

Existing Challenges and Future Directions in the Area of Plant Disease Recognition

Limited Data and Imbalanced Data Issues

Limited Data

The limited availability of labeled data poses a significant challenge in the field of vision-based plant disease recognition. Developing accurate and robust models for disease detection and classification often necessitates a substantial amount of labeled data. However, acquiring such data can be a time-consuming, expensive, and labor-intensive process Lheureux et al. (2017). There are several contributing factors to the scarcity of labeled data for plant disease identification:

- Expertise and time requirements pose significant challenges in accurately labeling plant disease images as it necessitates domain expertise and manual effort.

Table 10 Description and explanation of common evaluation metrics for plant disease classification, detection, and segmentation

Metric type	Name	Description	Equation
Classification	Accuracy	Measures the overall correctness of classification predictions	$ACC = \frac{TP+TN}{TP+TN+FP+FN}$
	Precision	Quantifies the proportion of correctly predicted positive samples out of all positive predictions	$P = \frac{TP}{TP+FP}$
	Recall	Calculates the proportion of correctly predicted positive samples out of all actual positive samples	$R = \frac{TP}{TP+FN}$
	F1-score	Harmonic mean of precision and recall	$F1 = 2 \cdot \frac{P \cdot R}{P+R}$
Detection	Intersection over Union (IoU)	Measures the overlap between the predicted and ground truth bounding boxes	$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}}$
	Average precision (AP)	Calculates the average precision from different confidence threshold of the Precision-Recall curve	$AP = \frac{1}{n}\sum_{i=0}^{n}(R_i - R_{i-1}) \cdot P_i$
	Mean average precision (mAP)	Averages the AP values across multiple classes or samples	
Segmentation	Pixel accuracy (PA)	Computes the percentage of correctly classified pixels	
	Dice coefficient	Quantifies the similarity between the predicted and ground truth segmentation masks	$DSC = \frac{2 \cdot \text{Intersection}}{\text{Predicted area} + \text{GT area}}$

Note: TP (true positive), TN (true negative), FP (false positive), FN (false negative), GT (ground truth)

Trained experts, such as plant pathologists, are essential for identifying and annotating disease regions in the images. However, this process can be time-consuming, particularly when dealing with extensive datasets or multiple plant species.

- Data collection poses significant challenges in acquiring a diverse and representative dataset that includes various plant species, diseases, and environmental conditions. The process typically involves field surveys and controlled experiments to capture images of both healthy and diseased plants. However, factors such as seasonal variations, limited accessibility to diseased plants, and the requirement for specific growing conditions can impede the data collection process.
- Annotation inconsistencies can arise during the labeling of plant disease images, as different experts may have varying interpretations of disease symptoms or boundaries Liu et al. (2021). This subjectivity in labeling can introduce inconsistencies in the annotated data, thus impacting the performance and reliability of trained models.

To address the limited labeled data challenge in plant disease identification, researchers have explored various strategies:

- Data augmentation: This involves artificially increasing the size of the labeled dataset by creating new images from existing ones. This can be done by applying transformations such as flipping, rotating, and scaling images Lheureux et al. (2017). By artificially increasing the size and diversity of the labeled dataset, these techniques enhance the model's generalization capabilities and effectively mitigate the risk of overfitting.
- Transfer learning: This involves using a model that has been trained on a large dataset of images, such as ImageNet, to initialize a model for plant disease identification Coulibaly et al. (2019); Chen et al. (2020). This can help to improve the performance of the model, even if it is trained on a limited dataset of labeled images.
- Collaboration and data sharing: Collaboration among researchers, organizations, and plant pathologists can facilitate the creation of shared datasets and resources Liu et al. (2021). Data sharing initiatives play a crucial role in making labeled datasets accessible, enabling researchers to develop more robust models and facilitate result comparisons across different datasets.

Imbalanced Data

In plant disease detection, data imbalance often arises from a long-tail distribution, where the majority class, representing healthy plants, typically outweighs the minority classes representing rare diseases Dang et al. (2021). This uneven distribution stems from several factors. Firstly, the vast diversity of plant diseases leads to varying disease prevalence. Secondly, the identifiaction of certain diseases differs, making them less likely to be labeled and included in training datasets. Thirdly, the scarcity of rare disease data often stems from the prohibitive costs associated with collection and labeling. The long-tail distribution can pose several challenges for plant disease detection:

- Biased model training: The overwhelming presence of healthy plant data can lead to models that are overly confident in predicting healthy plants and struggle to identify rare diseases Bhatia et al. (2020). This is because the model is trained on a dataset that is not representative of the real world, where rare diseases are more likely to occur.

- Poor recall for minority classes: Recall is the proportion of actual positive cases that are correctly identified as positive. For imbalanced datasets, recall for the minority classes is often poor, as the model is more likely to classify minority class examples as the majority class.
- Difficulty in evaluating model performance: Evaluating the performance of plant disease detection models can be difficult when there is a long-tail distribution because standard metrics such as accuracy may not be representative of the model's performance on the minority classes.

Several approaches can be used to address long-tail distribution and data imbalance in plant disease detection. These approaches include:

- Sampling techniques: Sampling techniques can be employed to balance the dataset by either oversampling the minority class or undersampling the majority class. Oversampling involves replicating instances of the minority class to increase its representation, while undersampling entails removing instances of the majority class to reduce its dominance. For instance, Divakar et al. (2021) tackles the long-tail distribution by employing Synthetic Minority Oversampling Technique (SMOTE) to perform oversampling and balance the dataset. They evaluate the performance using both F1 score and accuracy to identify the optimal classifier. Their findings reveal that EfficientNetB7 emerges as the top performer, achieving both high accuracy and F1 score. Additionally, it predicts whether a leaf image exhibits multiple diseases, further minimizing false predictions. However, the oversampling approach carries the drawbacks of increased computational overhead, potential noise introduction, and sensitivity to neighbor selection. In another study, Bhatia et al. (2020) implement a single feedforward neural network to predict tomato powdery mildew disease on an imbalanced dataset. To address the class imbalance, they applied random under-sampling and random over-sampling techniques prior to training the model. Their experimental results demonstrated that the model achieved the highest classification accuracy and AUC values of 89.19% and 88.57%, respectively, on the balanced dataset. While under-sampling approaches can reduce computational costs and mitigate the risk of overfitting, they may also discard valuable information, particularly if the minority class is already sparse.
- Deep generative models: Generative models, such as Variational Autoencoders (VAEs) Kingma and Welling (2013) or Generative Adversarial Networks (GANs) Goodfellow et al. (2020), can extract the underlying distribution of a large unlabeled plant dataset and synthetic plant images or data. Deep generative models have emerged as a powerful tool for addressing imbalanced datasets in plant disease. For example, GAN models, such as conditional GAN (C-GAN) Abbas et al. (2021) and fine-grained GAN Zhou et al. (2021), were implemented to generate synthetic images of healthy and diseased plant leaves. Figure 13 introduces the synthetic healthy and diseased plant leaves generated by the C-GAN model, which are realistic and can be used for training the disease detection model. The

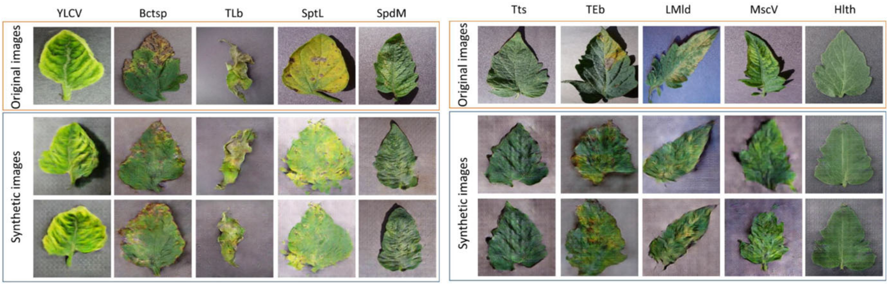


Fig. 13 The images displayed in the rows depict original tomato leaf images and synthetic leaf images created using the C-GAN structure proposed by Abbas et al. (2021). In row 1, the original tomato leaf images from five different classes are shown, including Yellow Leaf Curl Virus, Bacterial Spot, Late Blight, Septoria leaf spot, Two Spotted Spider Mite, Target Spot, Early Blight, Leaf Mold, Mosaic Virus, and Healthy. Rows 2 and 3 present synthetic images that correspond to the respective classes mentioned in row 1

authors showed that the GAN-based data generation approach helped augment the available dataset and alleviated the data scarcity problem.

- Class-weighting: JClass weighting assigns different weights to different classes during training, effectively giving more importance to the minority class. This helps the model to learn to pay more attention to the minority class and improve its performance on that class. For instance, Sambasivam and Opiyo (2021) used class weighting to improve the performance of a CNN model for classifying cassava leaf diseases. They found that the dataset they used was small and exhibited high-class imbalance, particularly biased towards Cassava Mosaic Disease and Cassava Brown Streak Virus Disease classes. By applying class weighting and focal loss to the CNN model, they were able to improve the accuracy by over 5% and reduce the log loss from over 20% (original model) to 0.06%.
- Ensemble learning: As explained in Section 4.3, ensemble learning involves training multiple models on different subsets of the data and then combining their predictions. Beside improving the performance of the final model, it has been proved to be an effective solution for solving the imbalanced dataset problem by improving the performance of the model on the minority classes. For example, Bruno et al. (2022) proposed a novel adaptive minimal ensembling approach that employs ensemble learning on feature vectors extracted from two EfficientNet-b0 weak models. Instead of aggregating the input as in traditional ensemble learning approaches, they utilized a trainable layer to combine the feature vectors. This method was evaluated on the PlantVillage dataset, achieving a remarkable accuracy of 100% for both the original and augmented versions.

Variability in Appearance

Variability in appearance presents a significant challenge in vision-based plant disease recognition. Plant diseases can manifest diverse visual symptoms, which can vary in terms of severity, location, color, shape, and texture OBrien (2017). This variability introduces difficulties in accurately identifying and classifying diseases based solely on visual cues. Several factors contribute to the variability in appearance of plant diseases:

- Disease types and stages: Different plant diseases can manifest in a wide range of visual symptoms, including leaf spots, discoloration, wilting, necrosis, deformations, and growth abnormalities. These symptoms can vary significantly in terms of severity, location, color, shape, and texture, making it challenging to establish consistent visual patterns for precise disease identification Singh et al. (2020a). Furthermore, diseases can progress through different stages, each with varying levels of symptom expression. This inherent variability poses a significant challenge in developing vision-based plant disease recognition systems.
- Plant species and cultivars: Variations in disease responses are a prominent feature of plant pathology, evident among different plant species and even within cultivars of the same species. These variations manifest in a spectrum of symptom types, intensities, and distributions Dang et al. (2023a). The distinct characteristics of each plant species and cultivar introduce complexity into the disease recognition process, posing a significant challenge for both traditional visual assessment and automated image-based methods Dang et al. (2023b).
- Environmental factors: The appearance of plant diseases is not solely determined by the invading pathogen; environmental factors play a significant role in shaping the course of disease development and symptom expression Dang et al. (2020b). Temperature, humidity, light exposure, and nutrient availability are among the key environmental factors that can influence the interaction between pathogens and their host plants. These factors can have a profound impact on the severity and presentation of disease symptoms. The same disease can manifest in various ways under different environmental conditions, making it challenging to establish consistent visual patterns for disease identification. This variability underscores the need for robust and adaptable plant disease identification systems that can account for the diverse range of symptom presentations across different environmental conditions.
- Co-occurrence of diseases: In the field of phytopathology, the complexities extend beyond single diseases Jeger et al. (2021). Instances of multiple diseases afflicting the same plant are not uncommon, presenting a formidable challenge in disease identification and management. The simultaneous presence of multiple diseases can lead to a perplexing interplay of symptoms, often overlapping or masking each other. Distinguishing individual diseases solely based on visual cues becomes increasingly difficult under such circumstances Gui et al. (2021). The co-occurrence of diseases further complicates the identification process due to potential interactions between the pathogens involved. Some pathogens may interact synergistically, exacerbating the severity of symptoms. Others may exhibit antagonistic interactions, leading to reduced symptom expression. These interactions introduce an additional layer of complexity to the already challenging task of disease identification.

To address the variability in appearance challenge, researchers and practitioners employ various strategies:

- Comprehensive image databases: Building large and diverse collections of images that include different disease types, stages, plant species, and environmental conditions is crucial. These databases play a crucial role in training models to recognize and generalize across a wide range of visual appearances, enabling robust performance in plant disease recognition. By immersing models in a vast array of visual representations of plant diseases, researchers equip them with the ability to recognize and classify diseases accurately, even when encountered in unfamiliar or challenging environments Russakovsky et al. (2015). This generalization capability is crucial for practical applications, ensuring that disease identification systems remain effective in practical settings.
- Feature engineering: The identification of informative and discriminative features from images is a critical step in the development of accurate plant disease detection systems. Researchers employ a variety of feature extraction techniques, including texture analysis, color histograms, shape descriptors, and DL-based feature representations, to capture the disease-specific characteristics that differentiate healthy plants from those afflicted by various ailments. The careful selection and combination of relevant features from these various sources is crucial for mitigating the impact of appearance variability and improving the accuracy of disease recognition. By effectively capturing the unique signatures of different diseases, researchers can develop robust models that can generalize effectively across a wide range of plant species, disease stages, and environmental conditions.
- Continuous learning and adaptation: Plant disease detection models can greatly benefit from embracing continuous learning and adaptation, enabling them to effectively address the inherent variability in appearance Thakur et al. (2022). By incorporating new data and retraining the models on a regular basis, researchers can equip them with the ability to learn from the latest trends and patterns in plant disease manifestation. This continuous learning process allows the system to dynamically adapt to emerging disease patterns, novel plant species, and evolving environmental conditions, ensuring that it remains relevant and effective in real-world applications.

To overcome the formidable challenge of variability in appearance for plant disease identification, researchers and practitioners must adopt a multifaceted approach, encompassing comprehensive datasets, advanced feature extraction techniques, and continuous learning strategies. By meticulously curating diverse visual representations of plant diseases and employing robust and adaptable ML models, they can significantly enhance the accuracy, reliability, and generalizability of vision-based plant disease identification systems.

Illumination and Occlusion Issues

The task of plant disease recognition using vision-based techniques is often hindered by the influence of illumination and occlusion, factors that can significantly impede the detection performance of these systems. Illumination variations, arising from changes in lighting conditions such as shadows, uneven lighting, or different times of the day

Yazdi and Bouwmans (2018), can profoundly impact the appearance of plant leaves and disease symptoms.

Insufficient illumination, in particular, can lead to poor contrast, loss of texture information, and reduced visibility of disease symptoms. This diminished visual information can obscure subtle patterns and nuances that are crucial for accurate diagnosis. The resulting decrease in detection performance can lead to misclassifications and missed opportunities for timely intervention.

Occlusion, another prevalent challenge, arises when parts of the plant, such as leaves or stems, are obscured by other objects or plant structures. This occlusion can hide disease symptoms from the detection system, making it difficult to assess the plant's health accurately. The presence of occlusion can also lead to false positives, as the obscured areas may mimic disease symptoms, potentially leading to unnecessary interventions.

Addressing the challenges posed by illumination and occlusion requires a combination of strategies. Image pre-processing techniques, such as histogram equalization and contrast enhancement, can be employed to improve the visibility of disease symptoms under varying illumination conditions. Occlusion detection algorithms can be utilized to identify and mask occluded regions, ensuring that disease symptoms are not overlooked Wang et al. (2021b).

Real-Time Plant Disease Detection

Real-time plant disease detection presents a formidable challenge due to the inherent complexities involved in processing large volumes of visual data in a time-critical manner Arsenovic et al. (2019). The analysis of high-resolution images or video streams captured from agricultural fields often requires extensive computational resources, posing a significant hurdle for real-time detection systems. These systems must strike a delicate balance between speed and accuracy, ensuring prompt and timely results without compromising the quality of disease identification.

The computational complexity of real-time plant disease detection is further exacerbated by the resource-constrained environments in which these systems must operate. Embedded systems and mobile devices Chen et al. (2021); Wang et al. (2022), commonly employed in field-based applications, often have limited computational power, memory, and energy resources. Developing efficient and lightweight algorithms that can run seamlessly on such platforms, without sacrificing detection accuracy, is a critical challenge.

To address these challenges, researchers are exploring various strategies. One approach involves utilizing hardware acceleration techniques, such as graphics processing unit (GPUs) and specialized ML accelerators, to offload computationally demanding tasks from the main processor, therefore improving processing speed and reducing energy consumption. Another strategy involves employing lightweight model architectures, specifically designed for resource-constrained devices, while maintaining acceptable levels of accuracy. These models often utilize techniques such as pruning, quantization, and knowledge distillation to reduce the number of parameters and computational complexity without compromising their ability to identify plant diseases effectively Khattab et al. (2019). Furthermore, researchers are investigating the application of transfer learning and domain adaptation techniques to leverage the knowledge gained from large, pre-trained models and adapt it to the specific task of plant disease detection in real-time settings. This approach can significantly reduce training time and improve the efficiency of real-time detection systems. Furthermore, researchers are investigating the application of edge computing, where processing and analysis are performed closer to the data source, resulting in reduced latency and faster detection. This approach can be particularly valuable in scenarios where real-time decisions are essential, such as autonomous agricultural systems or on-field monitoring Collinge et al. (2022).

Conclusions

Efficient and timely monitoring of crop diseases across large areas is crucial for assessing and managing plant protection. Traditional methods of disease detection, such as visual inspection by experts, are often time-consuming, labor-intensive, and subjective. CV has emerged as a valuable tool in this regard, enabling automated analysis of plant images to detect subtle visual indicators associated with diseases. Notably, the accuracy and efficiency of disease detection have witnessed remarkable improvements by harnessing ML and especially DL techniques. The application of CV techniques has revolutionized plant disease detection by offering several advantages. First and foremost, CV provides a non-invasive and non-destructive approach to diagnosis, eliminating the need for physical sampling or laboratory testing. Consequently, this not only reduces costs but also saves time and minimizes damage to plants. Moreover, CV-based systems excel at rapidly and accurately analyzing vast volumes of plant images, enabling the early detection of diseases. Early detection is essential for preventing disease spread and implementing targeted treatments or crop management strategies for effective control.

This review stands out for its comprehensive analysis of recent advancements in ML/DL techniques specifically applied to plant disease recognition based on publications from 2013 to 2023. This review categorizes and comprehensively analyzes the latest advancements in applying CV techniques to perform plant disease detection. Additionally, it offers potential solutions to tackle the challenges that arise during the implementation of these techniques. Therefore, this review serves as a valuable resource for researchers and industry professionals, fostering further innovation in the field.

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