Advances and Challenges in Computer Vision for Image-Based Plant Disease Detection: A Comprehensive Survey of Machine and Deep Learning Approaches

Syed Asif Ahmad Qadri, *Member, IEEE*, Nen-Fu Huang, *Senior Member, IEEE*, Taiba Majid Wani, and Showkat Ahmad Bhat, *Member, IEEE*

***Abstract*— As advancements in agricultural technology unfold, machine learning and deep learning approaches are gaining interest in robust plant disease identification. Early disease detection, integral to agricultural productivity, has propelled innovations across all phases of detection. This survey paper provides a meticulous examination of plant disease detection systems, elucidating data collection methodologies and underscoring the pivotal role of datasets in model training. The narrative navigates through the complex areas of data and image processing techniques, segueing into an exploration of various segmentation methods. The survey emphasizes the importance of feature extraction and selection techniques, illustrating their efficacy in increasing classification accuracy. It examines the classification process, embracing both traditional machine learning and avant-garde deep learning methods, with a particular spotlight on Convolutional Neural Networks (CNNs). The study examines over one hundred seminal papers, anatomizing their dataset utilizations, feature considerations, and classification strategies. Overall, the paper contemplates the challenges permeating this vibrant field, addressing critical issues such as dataset diversity, model generalization, and real-world applicability.**

***Note to Practitioners*—To ensure crop health and yield, timely and precise plant disease detection is crucial. Our research, titled "Advances And Challenges in Plant Disease Detection: A Comprehensive Survey of Machine and Deep Learning Approaches," examines the critical role of datasets, advanced image processing, and segmentation techniques in disease detection. This paper presents practitioners with a guide to the latest techniques for enhanced disease detection by emphasizing the significance of feature extraction and highlighting the capabilities of convolutional neural networks (CNNs). By understanding the highlighted challenges, such as dataset diversity and model generalization, industry professionals can better equip themselves to integrate these technological advancements into real-world agricultural applications.**

***Index Terms*— Plant disease detection, image processing, machine learning, deep learning, convolutional neural network.**

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Syed Asif Ahmad Qadri is with the College of Electrical Engineering and Computer Science, National Tsing Hua University, Hsinchu 300044, Taiwan (e-mail: syedasifahmadqadri@gmail.com).

Nen-Fu Huang is with the Department of Computer Science, National Tsing Hua University, Hsinchu 300044, Taiwan (e-mail: nfhuang@cs.nthu.edu.tw).

Taiba Majid Wani is with the Department of Computer, Control, and Management Engineering, Sapienza University of Rome, 00185 Rome, Italy.

Showkat Ahmad Bhat is with the Department of Computer Science and the Center of Innovative Incubator, National Tsing Hua University, Hsinchu 300044, Taiwan.

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I. Introduction

PRODUCING food is one of humanity's fundamental needs, and agriculture plays a significant part in both the functioning of the global economy and the fulfillment of this requirement. The agricultural industry is now confronting several issues, the majority of which can only be overcome through the implementation of information technology [1], [2]. Monitoring of the environment and remote control in agriculture is undergoing tremendous technological advancements, which are leading to the creation of agricultural instruments and systems that are more productive and lucrative. Both precision agriculture and intelligent agriculture are terms that are used to describe the practice of combining modern agricultural technology with more time-honored techniques to produce high-quality crops [3]. The production of crops is a substantial contributor to the overall output of agriculture, and it has experienced enormous shifts because of the proliferation of technical innovations [4]. To increase yield, contemporary agronomy makes use of the most advanced technical devices and methods, such as the application of contemporary instruments that facilitate the identification of environments that are optimal for the growth of bigger crop yields [5]. To boost production levels, researchers are conducting larger-scale experiments with genetically modified crops, engineered fertilizers, and pesticides [6].

The production of crops, however, encounters a significant obstacle in the shape of crop diseases [7]. This is true even though every other industry also experiences problems of some kind. Because of the enormous need for food across the world, it has become essential to place more emphasis on agricultural production. The whole yield will be shielded from any kind of loss before it is brought to the market, which is the purpose of this measure. Major crop yield losses can also be attributed to illnesses, in addition to natural disasters such as drought and earthquakes [8]. Yields are decreased because of the many kinds of plant diseases. This can be in the context of quality or the context of quality. Crop diseases are a serious concern in agricultural production systems because they reduce the quality and quantity of yields at every stage of the process, including production, storage, and transportation [9]. Reports on output losses because of plant diseases are extremely widespread at the farm level. In addition, crop diseases pose serious dangers to the safety of the world's food supply on a global scale. The accurate diagnosis of plant diseases is an essential component of effective management.

Plant diseases can be broken down into two major categories, infectious (biotic) and noninfectious (abiotic), based on the principal-agent that causes the disease in the plant [10]. Plants can contract infectious diseases from a wide variety of pathogens, such as fungi, bacteria, mycoplasma, viruses, viroid, nematodes, or parasitic flowering plants. Powdery mildew, for example, is caused by a fungal disease that can infect a wide variety of plants, including vegetables, fruits, and ornamentals [11]. These infectious agents can replicate within or on their host and move from one susceptible host to another. If the disease is not treated promptly, it will spread by fungal spores, which can be transported by the wind or rain, and it will cause substantial harm to the crop. On the other hand, noninfectious plant diseases are the result of unfavorable growing conditions. These conditions include extremes of temperature, moisture imbalances, toxic substances in the soil or atmosphere, and deficiencies or excesses of essential minerals [12].

Even though this is an age that is rich in technology and technology has advanced significantly, farmers still use the traditional and outdated method of determining which diseases are present in plants, which consists of the farmers visually and physically examining the plants with their own eyes. Disease symptoms, also known as the physical evidence of the presence of pathogens and the changes in the phenotype of the plants, can include a variety of things, such as spots on the leaves and fruits, wilting and color changes, curled leaves, etc., [9]. This antiquated method of studying and assessing plants with one's bare eyes and relying on the knowledge and expertise of the farmer presents a few challenges and obstacles. A farmer may be able to detect some plant infections and diseases that he is already familiar with using this method; however, the effectiveness of this method is limited when it comes to the detection of new plant diseases and diseases of plants that the farmer is not already familiar with. This results in the diseases of the plant going undiagnosed or in the application of the incorrect control strategy, both of which have the potential to influence the yield and, in the worst-case scenario, can result in the overall degradation of the plant. Certain diseases don't always present the typical symptoms [13], [14]. The capacity to recognize a disease requires knowledge of the typical growth patterns, varietal traits, and normal variability of plants within a species as these relate to the conditions under which the plants are growing. Historically, the diagnosis of diseases was carried out in the field by knowledgeable agronomists through the process of scouting [15]. On the other hand, this method relies entirely on visual inspection, which can be time-consuming.

As a result of recent developments in technology, there are currently sensing devices on the market that can detect unhealthy plants even before the observable symptoms of the disease manifest themselves [16]. The agricultural sector has been keeping pace with these technological breakthroughs, and as a result, farmers are now able to use platforms such as chatterbots to offer answers in their respective fields. It is anticipated that the use of artificial intelligence will expand dramatically in agriculture on a global scale [17], with the primary goal of improving the productivity of day-to-day farming activities through the implementation of technologies such as driverless tractors, drones, robots, and computerized irrigation systems [18]. Additionally, over the past few years, advancements in computer vision have been made, particularly in the field of machine learning techniques [19]. This has resulted in an enormous development.

In recent years, there has been a rise in the use of machine learning techniques in agricultural applications. This is a response to the growing demand for approaches that are both quick and precise, particularly in the areas of precision farming, agriculture, and food security. The field of machine learning examines strategies and procedures for programming computational programs that can alter or adjust their actions to get more accurate results. It provides computer systems with the ability to acquire knowledge and improve themselves naturally because of their experiences without having to be explicitly programmed.

Traditional machine learning methods require a stage known as feature engineering. This step requires the relevant features or qualities of the data to be manually selected and retrieved. This procedure might be time-consuming and calls for competence in the relevant field. Deep learning algorithms, on the other hand, can automatically learn and extract features from raw data without the need for any manual feature engineering on the part of the engineer. Because it enables the model to learn features directly from the raw pixel values of the image, deep learning has fundamentally changed the way image identification tasks are carried out. It is possible that the use of techniques from deep learning to the recognition of plant illnesses could considerably improve the detection of plant diseases. It is possible to automate the identification of plant illnesses and increase the accuracy of the detection process by combining these techniques with pattern recognition algorithms that evaluate data acquired from sensors [20]. This makes it possible to automate the identification of plant diseases. This could help farmers diagnose plant disease more quickly and precisely, which would lead to more successful treatment and preventative efforts. The development of image sensor technology has made it possible to perform real-time monitoring of plants and to generate images that may be applied to the diagnosis of specific diseases or the prediction of the symptoms of various diseases [21]. As a direct consequence of this, there has been an explosion in the amount of research that employs a wide variety of computational techniques and technologies in the process of identifying and monitoring plant diseases, to enhance disease management and control [22], [23]. This method has the potential to completely transform the agricultural industry by making it possible to diagnose plant diseases in a more timely and precise manner. As a result, crop yields will likely increase, and the production of food will become more environmentally friendly.

In recent years, there has been an increasing interest in the use of deep learning methodologies, specifically Convolutional Neural Networks (CNNs), for the development of high-performance artificial intelligence models for the identification of plant diseases. When used for IoT (Internet of Things) applications, these models have demonstrated encouraging results in terms of their accuracy and efficiency [24], [25]. CNNs are particularly useful for image-based research because of their ability to learn complicated low-level features directly from the image data. This makes CNN an excellent choice. Because of this, they are particularly beneficial for applications such as the detection of plant diseases, in which the traits of interest may be subtle and difficult to recognize using typical approaches to machine learning. The fact that lightweight CNN-based models can be used in IoT applications is one of the benefits of utilizing these models to identify plant diseases. Because these models can be adapted for usage on devices with limited resources, they are ideally suited for deployment in the field for real-time monitoring and detection of plant diseases [26]. This strategy has the potential to completely transform the agricultural industry by facilitating the early detection and efficient management of plant diseases, which will ultimately lead to increased crop yields and more environmentally responsible food production.

Even though there have been tremendous breakthroughs made in vision-based technologies for the identification of plant diseases, the detection of illnesses in real-world circumstances is still a difficult task. One of the primary reasons for this is that the backgrounds of the plants are quite complicated, and the conditions of their environments can change greatly from place to place. Vision-based models may have a more difficult time achieving accurate illness detection in the field because of these limitations. In-field applications of plant disease detection are also subject to constraints because of the necessity to consider variations in lighting, meteorological conditions, and the stages of plant development. The outward look of plants can shift noticeably over time, adding another layer of difficulty to the already challenging work of illness diagnosis. Researchers are investigating new methods that use various sensing modalities, such as hyperspectral imaging, thermal imaging, and acoustic sensing [27]. This is being done to address the issues that have been presented. Researchers can overcome the limits of approaches that are dependent on vision, which allows them to improve the accuracy and reliability of plant disease detection in real-world scenarios when they combine various modalities.

In Fig. 1, the graph sourced from the online portal "Dimensions.ai" illustrates the total number of publications related to "plant disease detection using deep learning" from 2014 to 2023. In 2014, the publication count started at a relatively modest figure of around 12,500. It experienced several fluctuations over the years, notably dipping in 2016 and 2019. However, a remarkable surge was observed from 2019 to 2021, peaking just above 30,000. This upward trajectory began to plateau in 2022, with a projected decline in 2023. This trend not only offers a visual representation of the escalating interest in this domain but also underscores the increasing research activity over the past decade. The pronounced growth in publications signifies the mounting recognition within the scientific community of the potential of deep-learning techniques in plant disease detection. Such advancements are critical in addressing the overarching challenges of crop health and food security, as the global research community endeavors to harness advanced machine learning methods for more precise and efficient plant disease detection and management solutions.

A. Contribution

The major contributions of this paper are as follows:

1. Comprehensive Integration of Recent Developments. This paper pioneers a holistic approach to plant disease detection by comprehensively integrating the latest developments in the field, including advancements in machine learning, deep learning, transfer learning, attention mechanisms, and image segmentation. Unlike previous surveys, this study encompasses a broad spectrum of recent research papers, shedding light on emerging trends and techniques that are shaping the future of plant disease detection.

2. Structured Comparison of Methods. We present a structured comparison of machine learning and deep learning methods used in plant disease detection, offering a unique perspective that aids researchers in making informed decisions regarding model selection. This comparison is meticulously designed to unravel the intricacies of each approach, providing clarity on their respective strengths and limitations in the context of plant disease detection.

3. In-depth Analysis of Image Segmentation. Our paper fills a critical gap in the literature by providing an in-depth analysis of image segmentation processes in plant disease detection. We delve into the challenges and breakthroughs in image segmentation, offering a comprehensive understanding of its pivotal role in accurately identifying plant diseases. This contribution is significant as it elucidates a fundamental component of disease detection that has been underexplored in previous studies.

4. Thorough Examination of Persistent Obstacles. By conducting a thorough examination of the persistent obstacles in plant disease detection, this survey enriches the research community's understanding of the field's complexity. Our analysis not only adds new insights to the existing body of knowledge but also serves as a catalyst for future researchers to tackle these challenges with a deeper and more nuanced approach. The exploration of these obstacles highlights the importance of continued innovation and research in overcoming the hurdles faced in plant disease detection.

The complete layout of this manuscript is shown in Fig. 2.

The organization of this paper is as follows. In Section II, we delve into the various types of plant diseases, with a particular focus on the distinct characteristics of fungal and bacterial diseases. Section III is dedicated to the exploration of plant disease detection systems, where we provide an in-depth analysis of the basic workflow for detecting plant diseases.

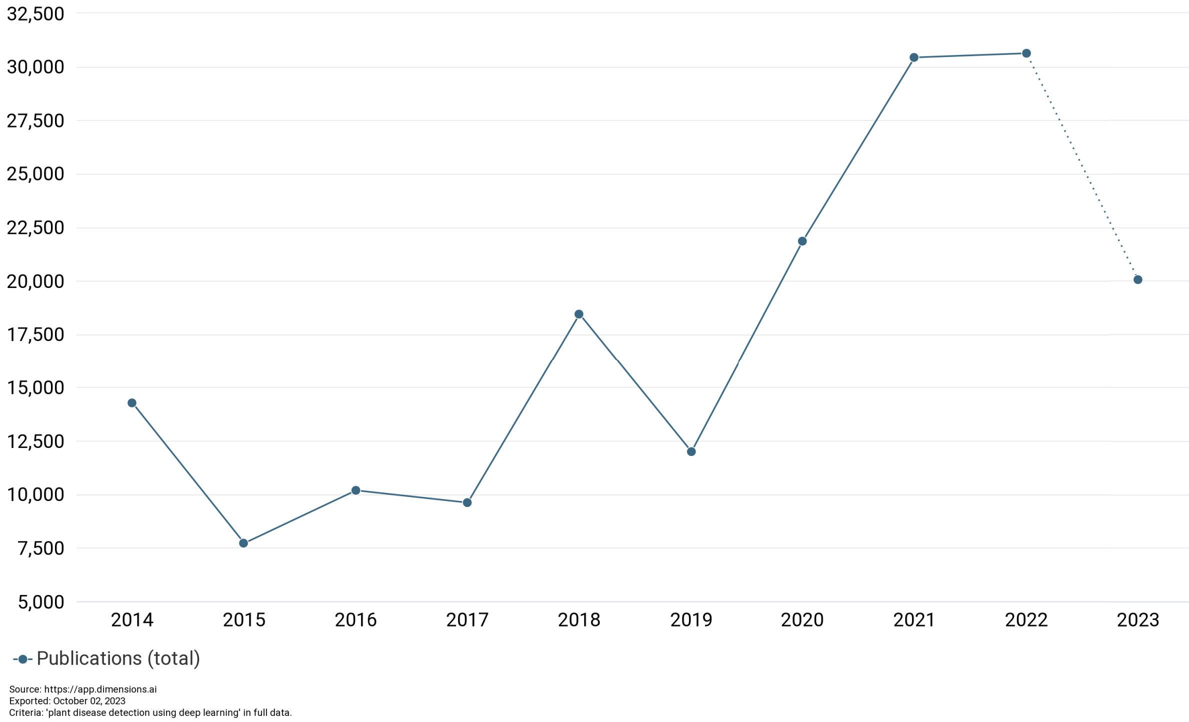


Fig. 1. Total number of publications related to "plant disease detection using deep learning" from 2014 to 2023.

Following this, Section IV presents an extensive literature survey, offering a comprehensive overview of recent studies that utilize a diverse range of machine learning and deep learning models for plant disease detection. In Section V, we highlight the current challenges faced in the field of plant disease detection. Finally, Section VI concludes the paper with a summary of our findings and insights.

II. Types Of Plant Diseases

Plant diseases occur due to causal factor that interferes with the normal functioning and structure of the plant, which in turn causes abnormal physiological processes to occur. Plant diseases are typically categorized according to the symptoms they cause or the physiological impact they have. However, some diseases can have identical symptoms despite being caused by different substances. Because of this, the strategies employed to control these diseases need to be diverse. The classification of illnesses according to their symptoms may also be insufficient, as a single causative agent may elicit many symptoms on the same plant organ, resulting in symptoms that overlap [28]. There are also other techniques of classification, such as categorizing diseases according to the type of plant that is afflicted, the vital process, or the function that is impacted. The technique of classification that is utilized the most frequently is based on the causal agent, with examples being infectious and non-infectious. When diagnosing plant diseases, host indexes are helpful, particularly for determining the pathogen that is responsible for a new disease that has been discovered on a host that is already well-studied [29].

Pathogenic organisms like viruses, viroid's, fungi, bacteria, nematodes, and parasitic flowering plants are responsible for the transmission of infectious plant diseases. These pathogens are obligatory parasites since they can only reproduce within the live cells of a specific host. A single plant species can be susceptible to several viral or viroid infections. The severity of the disease is typically greatest in plants that are propagated vegetatively, as opposed to sexually, through means such as cuttings or other plant material, rather than via seeds. An infectious agent can both reproduce within its host as well as spread to other hosts that are susceptible to the infection. The characteristics of several fungal and bacterial diseases that can affect plants are outlined in Table I.

Several environmental factors can lead to the development of non-infectious plant diseases. Some of these factors include an abundance or deficiency of light, water, vital soil nutrients, adverse soil conditions, severe temperatures, pesticides, and other chemicals. Because of the influence of ecological factors that are beyond the control of humans, it is frequently difficult to avoid or control these diseases, which can affect a wide variety of plant species [41]. Noninfectious diseases, in contrast to infectious diseases, are not brought about by pathogenic organisms and cannot be passed on to other people. After being exposed to the causative substance, symptoms may gradually arise over time. Additionally, adverse pre-harvest and storage conditions can also contribute to plant disease, which can ultimately result in considerable losses.

Detecting plant diseases using AI techniques can be a useful tool in the fight against crop loss. Traditional manual monitoring methods include agricultural professionals or farmers visually inspecting plant symptoms to look for signs of illness. This method can be time-consuming and there is no guarantee that it can accurately detect diseases in their earliest stages. To give a quicker and more accurate detection of plant diseases, automated solutions that are based on methodologies

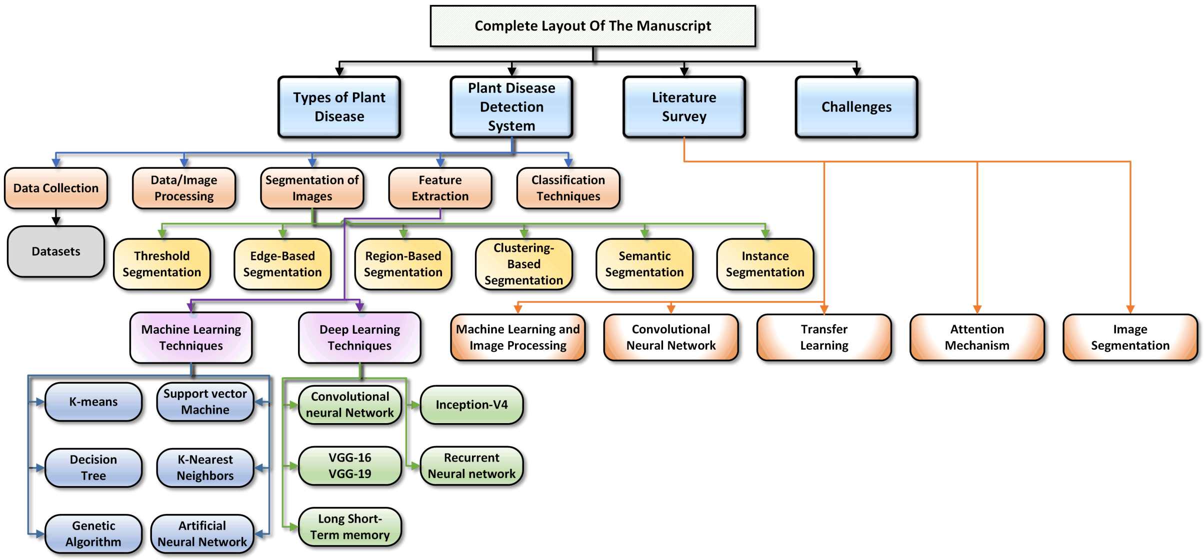


Fig. 2. Complete layout of the manuscript.

from the field of artificial intelligence have been created. The objective of AI techniques such as machine learning and computer vision is to achieve a level of precision comparable to that achieved by human specialists in the diagnosis of plant diseases [42]. To accomplish this goal, the systems are trained with a dataset of photos that includes both damaged and healthy plant specimens. The models acquire the ability to differentiate between the two different types of images because of this training, which enables them to recognize the disease in newly acquired photographs of plants. The trained models, in their most basic form, function as an efficient instrument for reliably diagnosing plant diseases.

Despite the significant progress made in the field of AI-based plant disease detection, there are still a few obstacles to overcome before real-time disease diagnosis can be accomplished in the field. One of the most significant obstacles is the wide range of environmental conditions that can be found across the country, which can play a role in the manifestation of plant diseases [43]. The accuracy of the automatic detection system can also be negatively impacted when there is debris on the plant's surface, such as soil, dust, or other particles of matter. In addition, poor nations frequently face difficulties in both the accessibility and the quality of the data required for the training of AI models. Either there is a shortage of photographs of diseased plants for the models to be trained on or the images themselves are not of a high enough quality. In addition, the expense of deploying these AI-based systems can be a barrier for small farmers, who may not have access to the necessary resources due to the nature of their businesses. Still, there is a significant opportunity for increasing crop output and decreasing losses caused by disease in the development and implementation of AI-based plant disease detection systems.

As shown in Fig. 3. We present a selection of images featuring both healthy and diseased plant leaves, taken from the PlantVillage dataset [44]. This visual comparison provides a clear example of the differences between a healthy leaf and a diseased leaf. It is crucial for understanding and training machine learning and deep learning for detecting plant diseases.

III. Plant Disease Detection System

Detecting diseases in crops is a crucial task for farmers to prevent significant crop losses. Traditionally, farmers would visually inspect their plants for signs of disease, but this method is subjective and prone to errors. To address this issue, a disease detection system using machine learning has been developed [42]. The plant disease detection system follows a set of general steps to identify diseases in plants. Initially, Internet of Things (IoT) sensors placed in the farm field will take pictures of the plants. These images are then processed and fed into machine learning models to classify the plants as healthy or infected. Machine learning algorithms analyze the images and use patterns and features to determine whether the plant is diseased or healthy. These algorithms are trained on large datasets of plant images, which allow them to accurately identify and classify different diseases. Once a disease is detected, farmers can take the necessary steps to treat the plants and prevent further spread of the disease.

The basic flow for plant disease detection typically involves several key steps, from data collection to disease detection, as shown in Fig. 4.

A. Data Collection

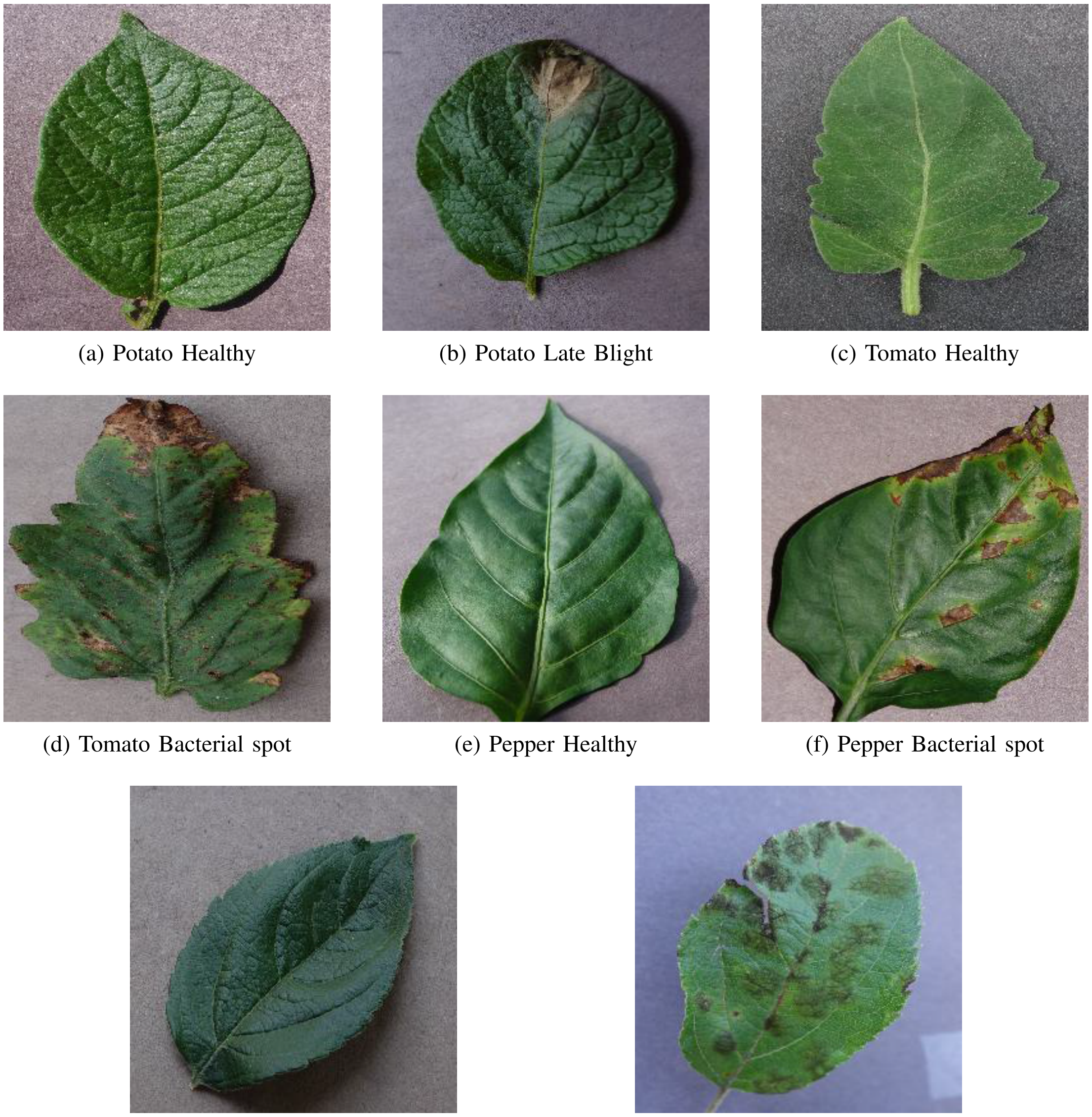
The first and most crucial phase in gathering information for APD is image acquisition. The act of obtaining a digital image of a situation is known as "image acquisition." An image is the term for this representation, and its constituent parts are known as pixels. An imaging sensor is the name given to the electronic equipment used to take a picture of a scene. The most common types of image sensors are charge-coupled devices (CCDs) and complementary metal oxide semiconductors (CMOS) [45]. Small analogic sensors

TABLE I
SEVERAL CHARACTERISTICS OF FUNGAL AND BACTERIAL DISEASES

DISEASE TYPE	DISEASE	HOSTS	PATHOGEN	SYMPTOMS	FEATURES
Bacterial [30]	Granville wilt	eggplant, tomato, pepper, tobacco, potato	Pseudomonas solanacearum	wilting of parts above ground, yellowing, stunting, become black or brown and roots decay	semitropical zones, occurs in most countries in temperate, causes crop losses.
Bacterial [31]	fire blight	apple and pear	Erwinia amylovora	Shrivel, stems, blossoms appear water-soaked causing rapid dieback and spread to leaves	first plant disease proved to be caused by a bacterium
Bacterial [32]	soft rot	many fleshy-tissue fruits e.g., cabbage, carrot, celery, onion	Erwinia carotovora	soft degeneration of fleshy tissues, resulting in mushy and soft tissues	causes major economic losses, occurs worldwide
Bacterial [33]	aster yellows	many vegetables, ornamentals, and weeds	Mycoplasma-like organism (MLO)	dwarfing malformations, chlorosis	carrots experience the most losses; transmission by leafhoppers
Bacterial [34]	citrus stubborn disease	citrus and stone fruits and vegetables	Spiroplasma citri (MLO)	shortened internodes, chlorosis, wilting yellowing of leaves	first MLO plant disease pathogen to be cultivated
Fungal [35]	late blight of potato	Potato	Phytophthora infestans	white mildew at the edge of lesions, water-soaked deep green to black or purple bottom leaf lesions with translucent green borders	caused starvation and death and mass migration of the population, responsible for the Irish famine;
Fungal [36]	black stem rust of wheat	wheat; many grasses	Puccinia graminis	Rust-colored pustules with spores appear on wheat, leading to the surrounding tissue turning yellow, followed by the formation of black teliospores. On barberry, infected tissue shows yellowing and abnormal growth, with the presence of orange spore masses	The disease is widespread wherever wheat is cultivated. In 1935, it devastated nearly 60% of the hard red spring wheat harvest in Minnesota and South Dakota. It is caused by a fungus with an intricate life cycle that involves both wheat and the barberry plant. Consequently, eradicating the barberry plant is a vital strategy for disease control.
Fungal [37]	coffee rust	Coffee	Hemileia vastatrix	centers turn brown and leaves fall, orange-yellow powdery spots on the lower side of leaves	in all coffee-producing nations, this disease has caused catastrophic losses.
Fungal [38]	apple scab	Apple	Venturia inaequalis	small olive-colored areas appear on young leaves, later turn black, and may coalesce; black circular spots appear on fruit	practically everywhere apples are produced; infection decreases fruit size and quality.
Fungal [39]	downy mildew	grapes, vegetables, grasses	many species of the family Peronosporaceae	downy fungus growth appears on the underside, yellow irregular spots appear on the upper leaf surface, leaves die	Bordeaux mixture, a combination of lime and copper sulfate used on grapes, was one of the first plant diseases to be managed by a fungicide.
Fungal [40]	wilts of vegetables, flowers, and some trees	alfalfa, cotton, shade trees potato, tomato	Verticillium species	similar to fusarium wilts; predominantly affect seedlings and cause rapid death; older plants are also affected.	widespread range: hundreds of plant species are infected.

may detect a certain wavelength of light and either significantly or negligibly increase their charge as a result. Specific hardware is used to amplify, filter, transfer, and improve these signals. Taking pictures only requires a lens and an appropriate output interface housed in the same device. All these parts work together to form the camera, the central component of computer vision systems. CCDs and CMOSs can both use a technique called time delay and integration (TDI) for acquiring images [46]. It makes a big difference in the capabilities of the camera. Inline monitoring, inspection, sorting, and remote sensing (for weather or vegetation observation) are all examples of applications that could benefit from TDI's combination of high speed and high sensitivity in low-light settings.

To ensure the models have enough data to learn and categorize plants as healthy or diseased, high-quality images must be acquired. The first stage in assuring quality is the image acquisition procedure, which directly affects the precision and correctness of the entire process. For data collection, researchers have utilized a wide range of cellphones, digital single-lens reflex (DSLR) cameras, and scanner devices. Devices known as unmanned aerial vehicles (UAVs) have also been put to use for data collection. At the Agricultural Scientific Innovation Base in the Information Institute of the Tianjin



(a) Potato Healthy (b) Potato Late Blight (c) Tomato Healthy

(d) Tomato Bacterial spot (e) Pepper Healthy (f) Pepper Bacterial spot

(g) Apple Healthy (h) Apple scab

Fig. 3. Comparative visualization of healthy and diseased leaf samples [44].

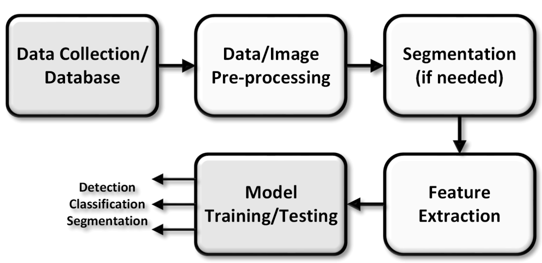


Fig. 4. Plant disease detection system.

Academy of Agricultural Sciences in Tianjin, China, Ma et. al., collected cucumber data using a Nikon Coolpix S3100 camera with a resolution of 2592 × 1944 pixels [47]. They used segmentation to differentiate between the foreground and the background of the image. Hu et. al., collected tea leaves at Tianjingshan National Forest Park, China, using a Canon EOS 80D SLR camera and DJI Phantom 4pro UAV at 10-m flight altitude [48]. Sun et al. [49] collected data in China with HySpex ODIN-1024 and UAV. Hyperspectral imaging uses spectrometers, lights, and CMOS cameras. In IoT applications, researchers have collected data using temperature, pressure, and humidity sensors. Since disease detection depends on many elements, digital cameras and other sensors can aid. In Taiwan's Central Weather Bureau and Bureau of Animal and Plant Health Inspection and Quarantine, Chen et. al., collected data using temperature, humidity, and barometric pressure sensors [50].

1) Datasets: Utilizing IoT-based capturing devices in agricultural areas that can capture periodic images of the crops is one method for determining whether plants are healthy or infected. These images can subsequently be utilized to train machine learning models to identify and classify various plant illnesses. To construct these models, researchers have compiled databases of plant photos that are accessible to the academic community and can be used by anybody interested. These datasets feature photographs with a variety of backgrounds and span a wide range of crop styles. The backgrounds of the photographs and the types of cropping that are included in the datasets are the two primary factors that may be used to classify the various datasets. Researchers have been hard at work compiling extensive databases that include a wide variety of plant species, including rice [51], maize [52], Apple [53], and many others. Furthermore, certain collections contain images with a variety of backgrounds, such as photographs taken in greenhouses, on farms, or in controlled conditions.

While some datasets are formed by taking pictures in a lab with backgrounds that are adjusted or eliminated, other datasets are made by taking pictures in agricultural fields. Additionally, certain datasets are produced for research on just one crop. These datasets are collections of photos of a single crop affected by a variety of diseases. Other dataset kinds include a range of crops, each featuring pictures of plants with a particular disease category known as multi-crop datasets. Table II lists some plant disease datasets with diverse crop diseases.

B. Data/Image Preprocessing

Image preprocessing plays a crucial role in the data collection phase for machine learning models, particularly in plant disease detection. This stage involves transforming acquired images into a consistent format through various techniques, such as resizing, color scale adjustments, noise and distortion removal, and enhancement. The main goal of this process is to highlight areas of interest within an image against a white background to reduce complexity and enhance the system's performance. A key preprocessing method is color space conversion, often using the Hue Saturation, and Value (HSV) system due to its close resemblance to human visual perception [61], [62]. This helps the machine to analyze images similarly to a human observer, increasing the effectiveness of the model. Furthermore, to expedite processing and improve accuracy, background removal and masking processes are typically utilized. The Hue component of the HSV model is predominantly used for further analysis [63]. Filtering processes, such as low-pass and high-pass filters, are applied to control the emphasis on certain areas of an image. The low-pass filter minimizes high-frequency components while the high-pass filter uses negative weighting coefficients to enhance regions with greater intensity gradients. The Laplacian filter is another tool that emphasizes contours and modifies gradient distributions in an image [64]. Other filtering techniques include the use of minimal and maximal filters that replace each pixel value with the smallest or largest value from the neighboring pixels, respectively [65]. The Fourier transform (FT) filter is also applied to transform the image into the spatial frequency domain [66].

Additionally, noise removal is a crucial aspect of image preprocessing, especially in real-time image capture scenarios. Numerous noise reduction methods such as mean [67], median [68], and Gaussian filters [69], along with Weiner filtering [70], have been previously utilized. To enhance plant disease images further, histogram equalization that redistributes image intensities is employed [71]. This technique is particularly useful in highlighting color variations within an image. The cumulative distribution function is also employed to distribute intensity values.

For higher accuracy in disease recognition, the segmentation of the diseased leaf image is performed to extract the disease spot images, which is critical before feature extraction [72].

C. Segmentation of Images

Image segmentation, a key component of digital image processing, plays an integral role in plant disease detection. It involves dissecting an image into distinct segments or objects based on their features and attributes. This practice aids in detailed object analysis, which in turn helps extract valuable features to distinguish between healthy and infected segments in plant leaves. After acquiring and pre-processing the images, they undergo segmentation to extract features critical for learning and classifying diseased leaves [73], [74]. The process of segmentation leverages a multitude of methodologies, which broadly fall into traditional and deep learning-based techniques.

Traditional segmentation techniques primarily employ classic computer vision algorithms to separate an image into various regions. These regions are determined by their attributes, such as color, texture, or intensity. These methods have long been the cornerstone of image processing and operate on the principles of mathematical models and heuristics to recognize and segment distinct objects within an image. Commonly employed traditional segmentation techniques in plant disease detection include threshold-based, edge-based, region-based, and cluster-based segmentation.

In the context of plant disease detection, these techniques have proven their worth by providing accurate and reliable identification of diseased segments. For instance, threshold-based segmentation can be used to separate healthy green areas of a leaf from areas showing discoloration due to disease [75]. Similarly, edge-based segmentation [76] can help outline the boundaries of a diseased area, while region-based segmentation [77] can isolate larger infected areas for further study. On the other hand, cluster-based segmentation [78] groups pixels that have similar properties into clusters, making it easier to separate healthy and diseased portions of a leaf. All these techniques aim to enhance the disease identification process by emphasizing the significant differences between healthy and diseased plant tissues.

Deep learning-driven image segmentation techniques capitalize on model training to amplify the system's proficiency in recognizing pertinent features. The prowess of deep neural network technology is particularly advantageous for image segmentation tasks. When it comes to diagnosing diseases in plants, two distinct variants of deep learning-based segmentation semantic segmentation [79] and instance segmentation [80] emerge as the preferred methodologies.

1) Threshold Segmentation: Threshold segmentation, often known as the image binarization process, is one of the simplest yet effective segmentation methods. It primarily involves the separation of the image foreground from the background based on grayscale values. This method excels at segmenting images

TABLE II
PLANT DISEASE DATASETS

DATASET	CROPS	CLASSES	DATASET SIZE	IMAGE BACKGROUND	LINK
Plant Village [44]	Apple Grape Soybean Raspberry Corn Squash Potato Strawberry Peach Blueberry Cherry Orange Pepper Bell Tomato	25	54,309	Laboratory	https://github.com/spMohanty/PlantVillage-Dataset
Apple Dataset [53]	Apple	4	1821	Field	https://www.kaggle.com/c/plant-pathology-2020-fgvc7/data
Plant disease detection database (PDDB) [54]	18 species	171	2326	Field and Laboratory	https://www.digipathos-rep.cnptia.embrapa.br/
XDB [54]	18 species	105	46,513	Laboratory	https://www.digipathos-rep.cnptia.embrapa.br/
PlantVillage (Extended) [55]	25 species	58	87,848	Field and Laboratory	
Citrus Images dataset [55]	Citrus Leaves and Fruits	5	759	Field	https://data.mendeley.com/datasets/3f83gxmv57/2.
LWDCD2020 [56]	Wheat	10	12,160	Field	
PlantDoc [57]	Apple, Bell Pepper, Blueberry, Cherry, Corn, Grape, Peach, Potato, Raspberry, Soyabean, Squash, Strawberry, Tomato.	17	2598	Field	https://github.com/pratikkayal/PlantDoc-Dataset
PDD271 [58]	Fruit plant/trees, Grains, and Vegetable plants	271	220,592	Field	https://github.com/liuxindazz/PDD271
Turkey-Plant Dataset [59]	Pear, Cherry, Walnut, Peach, Plum, Apple, Apricot.	15	4447	Field	https://github.com/mturkoglu23/PlantDiseaseNet
PLANTCLEF 2022 [60]	80000 Species	80	4 million	Field and Web images	https://www.imageclef.org/PlantCLEF2022
Casava dataset	Casava	5	24395	Field Images	https://www.kaggle.com/competitions/cassava-leaf-disease-classification
Hops disease Dataset	Hops Plant	5	1101	Field Images with non-uniform background	https://www.kaggle.com/datasets/scruggzilla/hops-classification
Corn or Maize disease dataset	Corn	4	4188	Laboratory	https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset
Rice Disease Dataset	Rice	5	5477	Field images with white background	https://www.kaggle.com/datasets/shayanriyaz/riceleafs
bean Leaf Dataset	Bean	3	1296	Field	https://github.com/AI-Lab-Makerere/ibean
Cucumber Plant Disease dataset	Cucumber	2	695	Field Images	https://www.kaggle.com/datasets/kareem3egm/cucumber-plant-diseases-dataset
PlantClef	10000 Species	20	11660	Field and Web Images	https://github.com/dusty-nv/jetson-inference/blob/master/docs/pytorch-plants.md

that exhibit a stark contrast between the foreground objects and the background [81]. However, for low-contrast images, an initial contrast enhancement is necessary before applying threshold processing.

Based on the chosen threshold values, threshold segmentation can be categorized into two main types:

a) Simple thresholding: This straightforward method involves replacing each pixel in an image with either black or white, depending on its intensity. If a pixel's intensity is lower than the threshold value, it's converted to black, and if it's higher, it becomes white. This method is a good starting point for those new to image segmentation [82].

b) Otsu threshold algorithm: This method, proposed by Nobuyuki Otsu, seeks to maximize the variance between the average grayscale levels of the foreground area, the background area, and the entire image [83]. This algorithm's simplicity and stability make it a popular choice for threshold segmentation. The steps of the Otsu algorithm are:

- Setting the threshold and categorizing pixels based on this value.
- Calculating the median for each cluster.
- Squaring the difference between the medians.
- Multiplying the number of pixels in one cluster by the number in the other cluster.

Vijai et al. [84] demonstrated the use of this algorithm by collecting a set of images from public directories, resizing them, and filtering out noise. They performed image segmentation using the Otsu and k-means algorithms. Finally, they extracted image features like contrast, correlation, energy, homogeneity, and average to classify the plant diseases.

2) Edge-Based Segmentation: Edge-based segmentation is a prevalent method in image processing that primarily focuses on the identification of object edges within an image. This is of paramount importance as edges typically contain a wealth of information crucial for analysis. Techniques employed in edge-based segmentation detect edges based on variations in texture, contrast, grayscale, color, saturation, and other attributes [85].

Edge-based segmentation methodologies are primarily classified into two categories:

a) Search-based edge detection: This method calculates a measure of edge strength and identifies local directional maxima of the gradient magnitude based on an estimated local orientation of the edge.

b) Zero-crossing-based edge detection: This approach identifies edges by searching for zero crossings in a derivative expression derived from the image.

Popular edge detection operators like Canny, Prewitt, Deroche, and Robert's Cross are often used after pre-processing the image to remove unwanted noise, simplifying the detection of discontinuities and edges [86].

3) Region-Based Segmentation: Segmentation techniques based on regions divide the image into segments that exhibit common characteristics. This method involves the identification of pixel groups, referred to as regions, by initially locating a seed point, which can be a small or large portion of the input image. Subsequently, these seed points expand by incorporating more pixels or contracts to combine with other seed points [87].

Region-based segmentation is further classified into two main types:

a) Region growing: This technique at the pixel level begins with the selection of seed points. The region expands by considering factors such as pixel intensity, grayscale, color, adjacency, and similarity. The procedure then proceeds to segment the complete image into pattern cells, establishing connections between neighboring cells and merging them according to their intensity value similarities. This growth of the region persists until there are no more regions left that can be merged.

b) Region splitting and merging: This method simultaneously splits and merges parts of an image. It first divides the image into regions of similar attributes and then merges adjacent portions that resemble each other. Unlike region growing, which focuses on a particular point, region splitting considers the entire image [88]. Following a divide-and-conquer strategy, the algorithm divides the image into different sections and matches them based on predetermined conditions.

4) Clustering-Based Segmentation: Clustering algorithms are used to partition the image into separate sets of pixels known as clusters, where pixels within each cluster exhibit similar features. Well-known clustering algorithms encompass fuzzy c-means (FCM), k-means, and enhanced k-means algorithms.

a) K-means clustering: The K-means algorithm is an iterative process designed to divide a dataset into K predefined, separate, and non-overlapping subgroups, with each data point belonging to just one group. Its objective is to maximize the similarity among data points within the same cluster while ensuring clear distinctions between clusters [89]. The algorithm continues to iterate until there are no further changes in the centroids. K-means finds widespread use in a range of applications, such as market segmentation, document clustering, image segmentation, and image compression.

b) Fuzzy C-means: The fuzzy c-means clustering method allows pixels to be part of multiple clusters, with each pixel exhibiting different degrees of similarity with each cluster. The algorithm utilizes an optimization function that influences the accuracy of the results [90].

5) Semantic Segmentation: Semantic segmentation is an advanced image segmentation technique that involves classifying individual pixels in an image into different semantic classes. Each pixel is assigned to a specific class without considering any contextual information. The objective of semantic segmentation is to extract meaningful features from the image and categorize them into distinct classes [91]. The process typically involves analyzing training data, creating a semantic segmentation network, and training the network to group pixels in the image and generate a segmentation mask.

Semantic segmentation plays a crucial role in localizing and identifying specific objects of interest, such as diseased regions on plant leaves. By training a network to recognize and segment these regions, it becomes possible to accurately classify and diagnose plant diseases based on the segmented areas. This approach enables precise identification and targeted treatment, leading to improved plant health and crop yield.

6) Instance Segmentation: Instance segmentation is a more advanced form of image segmentation that not only identifies and delineates objects but also distinguishes each distinct instance of an object in an image. It combines the functionalities of object detection and semantic segmentation. Instance segmentation involves detecting and localizing multiple instances of different object classes in an image while delineating the boundaries of each instance at a detailed pixel-level wait [92].

The instance segmentation process typically consists of two key steps. Firstly, object detection is performed to identify all bounding boxes for the objects in the image. Secondly, a semantic segmentation model is applied within each bounding box to achieve detailed segmentation of the object instances.

D. Feature Extraction

Feature extraction is a crucial step in computer vision techniques used for the automatic detection of diseases in plants [93]. It involves extracting relevant and informative features from raw images while reducing redundancy. Different feature extraction methods focus on specific image properties such as texture, shape, size, color, pattern, and edges. The choice of features is important to achieve accurate results in plant disease analysis.

There are two main types of feature extraction techniques: handcrafted feature engineering and deep learning feature extraction. Handcrafted features involve manually designing and selecting features based on domain knowledge. Deep learning techniques, on the other hand, learn feature representations automatically from data using neural networks.

Feature extraction techniques offer numerous advantages in the realm of plant disease detection. They enhance data visualization, accelerate model training, and elevate model accuracy. By appropriately extracting and selecting features, a robust and efficient disease analysis system can be developed. In the domain of plant disease detection, diverse categories of features play pivotal roles. Color features elucidate the visual attributes of an object and can be quantified through color histograms and color co-occurrence matrices. Texture features encapsulate surface characteristics such as uniformity, entropy, energy, contrast, and correlation, and are obtainable through methods like Local Binary Patterns (LBP), Gabor filters, and Gray-Level Co-occurrence Matrices (GLCM) [94]. Shape features delineate the contour of an object and can be gauged by attributes like orientation, area, eccentricity, and centroid, with techniques like Hu's moments frequently employed. The amalgamation of color, texture, and shape attributes has the potential to enhance the performance of disease classification systems. In certain cases, a single type of attribute may be insufficient for accurately characterizing an object. For this reason, visual descriptors based on MPEG-7, which encompass texture, color, and shape features, can be utilized to address this need [95].

However, handcrafted features have certain limitations. Visual similarities in symptoms of different diseases can make it challenging to extract appropriate features that can differentiate or identify diseases accurately. Handcrafted features may perform well under specific setups and constraints but degrade significantly with variations in setup or conditions. Additionally, different growth stages of plants and crops can be affected by similar or different diseases, requiring different sets of features at different stages. To address these challenges, deep learning-based feature extraction techniques have emerged. Deep learning models can automatically learn relevant features from data, adapt to varying conditions, and handle complex visual similarities. This reduces the reliance on handcrafted features and improves the robustness of disease detection systems.

In machine learning-based applications, it is crucial to select the most suitable features from the available set to avoid computation complexity and overfitting. Feature selection strategies, such as Principal Component Analysis (PCA) which calculates entropy, covariance, and feature scores, can help identify the most relevant features [96]. Other feature extraction methods like Speeded-Up Robust Features (SURF) [97], Histogram of Oriented Gradients (HOG) [98], Scale-Invariant Feature Transform (SIFT) [99], and Pyramid Histogram of Visual Words (PHOW) [100] have also shown promising performance in plant disease detection.

E. Classification Techniques

Classifying plant diseases plays a crucial role in the field of computer vision, where the goal is to categorize input data, such as images of plant leaves, into specific classes based on the presence or absence of identified diseases [101]. Researchers employ both machine learning (ML) models [102] and deep learning (DL) models [103] to gain valuable insights into the data, revealing relationships between various factors affecting the occurrence of plant diseases. Following data preprocessing and feature extraction, ML/DL models are used for tasks like classification and regression. The selection of appropriate classifiers holds significant importance in the context of plant disease classification.

1) Machine Learning Techniques: Machine learning (ML) methods are categorized into two main groups: supervised and unsupervised techniques. In supervised methods, models are trained using labeled data, which means both the input data and their associated outputs are known. The model learns from this labeled data and can predict outcomes for new, unseen input data. In contrast, unsupervised techniques involve training models with unlabeled data, with the objective of uncovering patterns or structures within the data. The detection of plant diseases relies on the application of several widely used classifier techniques. They include:

Several commonly used classifier techniques are employed in the detection of plant diseases. These include:

a) K-means: K-means K-means, an unsupervised learning algorithm, is employed for clustering purposes. It divides data points into a predetermined number of clusters according to their resemblances. In the context of plant disease detection, K-means can be utilized to group similar plant images, facilitating the recognition of patterns or clusters rooted in their extracted features [104].

b) Support vector machine (SVM): SVM (Support Vector Machine) is a frequently employed supervised learning algorithm for classification purposes. It aims to identify the optimal hyperplane that effectively separates various classes of data points. In the context of plant disease detection, SVM is trained with labeled data to classify plant images, distinguishing between healthy and infected specimens based on their extracted features. In a study conducted by Bhatia and colleagues [105], they utilized a hybrid model that incorporated a Support Vector Machine (SVM) for the detection of powdery mildew disease in tomato plants.

c) Decision tree: A decision tree is a supervised learning algorithm applicable to classification and regression tasks. It constructs a tree-shaped model that represents decisions and their associated outcomes. In the realm of plant disease classification, a decision tree is trained with labeled data to categorize leaves into distinct disease groups based on their unique features [106].

d) Random forest (RF): Random Forest, as an ensemble learning method, combines multiple decision trees to boost predictive accuracy and resilience. Each tree individually classifies input data, and the final classification is determined through majority voting. In plant disease classification, Random Forest is used by training it on labeled data and harnessing the collective decision-making of multiple trees [107].

e) K-NN (K-Nearest neighbors): K-NN (K-Nearest Neighbors) is a straightforward yet highly effective supervised learning algorithm. It categorizes new data points by considering the majority class of their k closest neighbors in the training dataset. In the context of plant disease classification, K-NN is applied to assign labels to new plant images based on the labels of similar images within the training set [108].

f) Genetic algorithm (GA): Genetic algorithms are optimization techniques inspired by natural evolution processes. They are employed to find the optimal set of features or parameters for a given problem. In plant disease classification, GA helps select the most informative features for accurate disease detection [109].

g) Artificial neural network (ANN): Artificial Neural Networks (ANNs) are computational models inspired by the intricate network of neurons in the human brain. These networks are interconnected artificial neurons that are designed to learn and adapt through training. In the context of plant disease detection, ANNs are used to capture and understand the complex patterns and relationships existing between various input features and the different classes of plant diseases. By processing and learning from a vast amount of labeled data, ANNs become proficient at recognizing the distinct characteristics associated with each disease, enabling accurate and automated classification of plant health [110]. This technology has proven to be a valuable asset in precision agriculture, aiding in the early identification of diseases and contributing to more effective crop management and yield optimization.

2) Deep Learning Techniques: Deep Learning (DL) is a subfield of machine learning that harnesses Artificial Neural

Networks (ANN) to address intricate problems. It offers notable advantages compared to traditional machine learning techniques, as it autonomously extracts pertinent features from raw data, eliminating the need for manual feature engineering. In the domain of plant disease detection, DL methodologies have brought about a significant improvement in accuracy and overall performance.

a) Convolutional neural networks (CNNs): One key component of DL is Convolutional Neural Networks (CNNs). These networks are meticulously tailored for image-related tasks and have emerged as the cornerstone of deep learning approaches for image classification. CNNs utilize convolutional layers to progressively extract meaningful features from images. Early layers focus on basic elements like edges and textures, while subsequent layers uncover more intricate and abstract features. This hierarchical feature extraction capability empowers CNNs to discern specific patterns and structures within images, rendering them exceptionally effective in the realm of plant disease detection [111].

b) Inception-V4: Inception-V4 is an advanced CNN architecture that builds upon the original Inception model. It consists of both asymmetric and symmetric blocks, enabling the network to efficiently learn feature maps and compute features across different spatial scales. By employing techniques such as average pooling and maximum pooling, Inception-V4 reduces computational costs while preserving accuracy. Researchers have combined Inception-V4 with other models like AlexNet to enhance plant disease diagnosis accuracy by utilizing the strengths of different architectures [112].

c) VGG: VGG-16 and VGG-19, developed by the Visual Geometry Group at Oxford University, have achieved remarkable performance in image recognition tasks. These models are known for their simplicity and deeper architecture. VGG-16 comprises multiple convolutional and pooling layers, followed by fully connected layers and a SoftMax layer for classification. VGG-19 extends VGG-16 by adding three additional convolutional layers, enabling more effective image identification. Researchers have leveraged pre-trained VGG models as classifiers, feature extractors, and fine tuners in various experiments related to plant disease detection [113], [114].

d) Recurrent neural networks (RNNs): RNNs are suitable for analyzing sequential data, including time series data. RNNs can capture temporal dependencies and extract features automatically from the data. However, RNNs can suffer from gradient-related issues, such as exploding or vanishing gradients, which can hinder training. To address this, attention-based RNNs have been used in plant disease detection. These models automatically identify and focus on infected regions within images, extracting relevant features to improve disease classification accuracy [115].

e) Long short-term memory (LSTM): LSTM networks are a variant of RNNs that address the challenge of capturing long-term dependencies. Standard RNNs struggle to retain information over long sequences, but LSTM cells have a unique memory mechanism that allows them to selectively remember or forget information. This property makes LSTM networks particularly effective in processing time-dependent problems. For instance, LSTM networks have been employed to establish relationships between meteorological data and pest occurrences, enabling the forecasting of future pest attacks [116].

Deep learning methods, including CNNs like Inception-V4 and VGG models, as well as RNN variants like attention-based RNNs and LSTM networks, have revolutionized plant disease detection. These methods automate the feature extraction process, capture temporal dependencies, and achieve high accuracy in classifying plant diseases. Their applications have greatly advanced the field by enabling researchers to analyze raw images, identify patterns, and diagnose diseases more effectively. With the combination of computer vision advancements, hardware technologies, and deep learning techniques, the accuracy and efficiency of disease detection systems in agriculture have been significantly enhanced.

IV. LITERATURE SURVEY

The field of plant disease detection represents a pivotal axis around which the productivity and quality of agricultural yield hinges. Traditional methodologies, leveraging image processing (IP) and machine learning (ML) algorithms, have, to an extent, catered to this need. However, these techniques often pose challenges in terms of accuracy, computational efficiency, and manual intervention, accentuating the need for more robust and automated solutions.

Recent advancements in deep learning, specifically Convolutional Neural Networks (CNNs), have initiated a paradigm shift in this domain. These end-to-end learning models have demonstrated enhanced accuracy and automation, predominantly due to their capability to learn distinctive disease patterns from pixel-level data. Various CNN architectures, such as VGGNet, ResNet, InceptionNet, and DenseNet, have been extensively studied and tailored for this task. Yet, the computation-intensive nature of these models can be a limiting factor, particularly in resource-constrained environments. To mitigate such computational challenges, the research has pivoted towards lightweight CNNs that offer comparable performance while significantly reducing computational overhead. Moreover, the transfer learning approach has been adopted as a viable solution to tackle the limitation of sparse labeled training data, by leveraging pre-trained models on larger, generic datasets and fine-tuning them for plant disease detection. Further, ensemble learning techniques have been utilized to harness the collective intelligence of multiple models, thereby improving the robustness and accuracy of the predictions. The incorporation of attention mechanisms in CNN models represents another significant stride in this domain, providing models with the capability to focus on relevant disease-specific features while making predictions.

In this section, we provide a comprehensive survey of the myriad of studies published in recent years, which exploit a wide array of machine learning and deep learning models for plant disease detection.

A. Image Processing and Machine Learning (IP and ML)

In the past two decades, image processing (IP) techniques have displayed considerable potential in the realm of plant disease identification. As machine learning (ML) has continued to evolve, researchers have integrated a diverse range of classification and clustering methods along with image preprocessing algorithms into their workflows.

Early efforts to identify plant diseases primarily relied on traditional IP techniques. However, over the past decade, ML-based methods have gained momentum, propelled by advancements in other domains. In the initial stages, traditional IP algorithms such as local binary patterns (LBP) and histograms were commonly employed. Among the many ML algorithms, prominent choices for researchers in developing disease detection models include Support Vector Machine (SVM) [117], Artificial Neural Network (ANN) [118], particle swarm optimization (PSO) [119], Naive Bayes [120], k-means clustering [121], simple linear iterative clustering (SLIC) [122], and expectation—maximization (EM) [73].

Table III provides a frequency chart outlining the prevalence of these crucial methods across various articles, shedding light on the performance of these approaches in detecting plant diseases. Researchers have utilized multiple metrics to assess the effectiveness of these methods on diverse datasets. This shift towards ML-based disease detection methodologies underscores the growing importance of combining IP techniques with advanced machine learning approaches in the field of plant pathology. These tools hold great promise for the future of precision agriculture and crop management.

Ramesh et al. presented a methodology utilizing Random Forest for the differentiation between healthy and diseased leaves based on created datasets [107]. The approach involved dataset creation, feature extraction employing Histogram of an Oriented Gradient (HOG), classifier training, and classification. The algorithm's primary goal was the detection of plant diseases in greenhouse or natural settings, capturing images against plain backgrounds to minimize occlusion. Comparative analysis with other machine learning models showcased a 70% accuracy rate using 160 papaya leaf images.

Ahmed et al. presented a machine learning system to identify three significant rice plant diseases: brown spot, leaf smut, and bacterial leaf blight [123]. Their approach involved using high-quality images of afflicted rice leaves set against a white background, complemented by preprocessing techniques. They applied a range of machine learning algorithms, including Logistic Regression, KNN, Naive Bayes, and Decision Tree (J48), to train the dataset. After subjecting the dataset to 10-fold cross-validation, the Decision Tree algorithm exhibited remarkable performance, achieving an accuracy rate of over 97%. This success opens the door for further research with enhanced datasets, and promising advancements in disease detection.

Ganatra and Patel introduced a predictive model aimed at detecting and classifying plant leaf diseases, employing a combination of computer vision and machine learning techniques [124]. The process encompassed various stages, including preprocessing, segmentation, and the extraction of diverse leaf features such as veins, texture, shape, and color. The study compiled an extensive dataset comprising 14,956 images distributed across 38 classes. They employed multiple machine learning classifiers, including Artificial Neural Network, Random Forest, K-Nearest Neighbor, and Support Vector Machine, for the classification task. The results were thoroughly assessed and compared, revealing that Random Forest stood out among the classifiers, achieving an accuracy of 73.38%, an F-Score of 71.98%, a recall of 72.90%, and a precision of 72.88%.

Kulkarni et al. introduced a computer vision-based system for efficient plant disease detection, achieving an impressive average accuracy of 93% and an F1 score of 0.93 [125]. The proposed technique combined statistical image processing and machine learning, offering a smart and effective approach for detecting 20 different diseases across five common plant species. This system demonstrated both high accuracy and computational efficiency, showcasing its potential for practical applications in crop disease detection.

Harakannanavar et al. utilized a precise algorithm integrating machine learning and image processing techniques for the early identification of leaf diseases [126]. The process initiated with the resizing of tomato leaf samples and enhancement of their quality through Histogram Equalization. Employing K-means clustering, they partitioned the data space into Voronoi cells, while contour tracing facilitated the extraction of leaf boundaries. Machine learning approaches, including Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbor (K-NN), were employed for feature classification, yielding impressive accuracy rates of 88%, 97%, and 99.6%, respectively, when applied to disordered tomato samples. The proposed model harnessed computer vision techniques and demonstrated superior performance, particularly with the CNN approach.

Zamani et al. focused on evaluating infected leaf disease images and proposed an automated leaf disease detection system for precision agriculture [127]. The system comprised image acquisition, pre-processing, segmentation, feature extraction, and machine learning techniques. Segmentation was achieved using the K-Means method, followed by feature extraction through Principal Component Analysis. Disease classification was performed using various algorithms, including RBF-SVM, SVM, random forest, and ID3. RBF-SVM demonstrated superior performance in accurate leaf disease detection.

Ansari et al. introduced an innovative approach that integrated support vector machine (SVM) with image processing to effectively detect and classify grape leaf diseases [128]. The proposed framework involved crucial steps, including image capture, denoising, enhancement, segmentation, feature extraction, and classification. Image denoising was carried out using the mean function, and image enhancement utilized the CLAHE method. Image segmentation was achieved through the application of the Fuzzy C Means algorithm, while relevant features were extracted using Principal Component Analysis (PCA). For the classification and detection processes, various algorithms were employed, including PSO SVM, BPNN, SVM, and random forest. Notably, the PSO SVM achieved a higher level of accuracy, approximately 97.5%, in effectively classifying and detecting grape leaf diseases.

Ahmed and Yadav investigated the potential of GLCM-based crop categorization using textural information in greyscale images [129]. The objective was to assess the significance of textural elements in distinguishing crop categories, especially in less detailed greyscale images. Various machine learning algorithms, including Naive Bayes, random forests, SVMs, feed-forward neural networks, and neural networks, were employed for crop categorization and plant disease detection. These models aimed to predict disease detection in the early stages, enabling preventive actions and predictive maintenance. The study achieved a high accuracy of 97.5% for textural-based images using NB and random forest classifiers with five classes. The ensemble plant disease model outperformed other proposed models, showcasing its potential for early disease detection in plants.

Sahu and Pandey introduced a novel Hybrid Random Forest Multiclass SVM (HRF-MCSVM) model for plant foliar disease detection, enhancing computation accuracy by preprocessing and segmenting image features with Spatial Fuzzy C-Means [130]. The system was evaluated using the Plant Village dataset, comprising 54,303 healthy and diseased leaf images. Performance metrics such as accuracy, F-measure, specificity, sensitivity, and recall value were utilized to assess system effectiveness. The proposed HRF-MCSVM method was compared against existing techniques like BRBFNN, SVM, ABCO, and DBN, demonstrating superior accuracy of 98.9% and improved diagnostic capabilities in detecting various leaf diseases.

Prabu and Chelliah addressed the significant issue of plant leaf disease detection, which poses a considerable threat to agricultural productivity in India [131]. The authors introduced a novel approach, the Boosted Support Vector Machine-based Arithmetic Optimization Algorithm (BSVM-AOA), to accurately detect and classify diseased plant leaves. The methodology involved image segmentation using the vector-valued active contour model and feature extraction via the greyscale co-occurrence matrix. Results demonstrated that the proposed BSVM-AOA approach outperformed others with an accuracy rate of 98.6%.

Acharya et al. highlighted the shift towards automated machine learning-based approaches for plant disease detection, which offer non-invasive methods with higher detection accuracy and faster results compared to invasive techniques [132]. The authors focused on disease detection by identifying affected areas in leaf images, conducting feature extraction, and employing Support Vector Machine (SVM) and Least Square SVM (LS-SVM) for classification. LS-SVM demonstrates superior accuracy, achieving 91% for DS1 and 98.85% for DS2, compared to SVM.

B. Convolutional Neural Networks (CNN's)

Plant disease detection has greatly benefited from the advancements brought about by Convolutional Neural Networks (CNNs). In this context, CNNs have emerged as a powerful tool for analyzing digital images and have significantly contributed to research in the field of plant disease detection. Compared to traditional machine learning algorithms, CNNs have proven to be more effective in this domain [133]. This superiority stems from their ability to automatically learn and extract relevant features from input images, without requiring explicit feature engineering. By leveraging their deep learning capabilities, CNNs can identify intricate patterns and subtle visual cues associated with various plant diseases.

One of the key advantages of CNNs in plant disease detection is their inherent ability to exhibit invariance to translation, scale, and rotation [134]. This characteristic allows CNNs to generalize well across different plant species, environmental conditions, and imaging variations. Consequently, CNN-based models can provide more accurate and reliable detection results, even when confronted with varying conditions. Furthermore, the scalability of CNNs enables them to handle large datasets and high-resolution images, which is crucial in the context of plant disease detection. With datasets often comprising thousands or even millions of images, CNNs can effectively process and analyze this wealth of data [135]. This capability enables researchers and practitioners to gain insights into the complex relationships between visual symptoms and disease conditions, leading to improved detection and diagnosis. The pertinent literature has been succinctly encapsulated in Table IV, providing a comprehensive overview of the key elements such as the datasets employed for the experiments, the specific convolutional neural network (CNN) models utilized, and the corresponding accuracy metrics.

Wallelign et al. investigated the feasibility of utilizing Convolutional Neural Networks (CNN) for the identification of plant diseases in leaf photos captured within their natural habitat [136]. To classify soybean plant diseases, they proposed a model based on the LeNet architecture. They sourced 12,673 samples from the PlantVillage database, comprising leaf photos categorized into four classes, including images of healthy leaves. The model they presented demonstrated an impressive classification accuracy of 99.32%. Similarly, Geetharamani et al. introduced a 9-layer deep convolutional neural network (Deep CNN) [137]. They utilized an open dataset featuring 39 distinct classes, containing 49,598 plant leaf images along with background images from the PlantVillage dataset to train the Deep CNN model. Their proposed model effectively categorized the testing set of plant leaf images, achieving an average accuracy of 96.46%. Furthermore, it exhibited high accuracy levels ranging from 92% to 100% for each individual class.

Yadhav et al. proposed and evaluated the activation functions for CNN models in real-time plant disease detection [138]. The study achieved an improved accuracy of 95% as well as increased training speed by 83%. Additionally, the use of K-means clustering helped optimize fertilizer usage based on the affected areas.

Kumar et al. introduced a deep learning-based approach employing three main architectures: Region-based Fully CNN (R-CNN), Single Shot Multibook Detector (SSD), and Faster Region-based Convolutional Neural Network (Faster R-CNN) [139]. They analyzed a dataset of over 50,000 images, each labeled among 38 different classes, sourced from the Plant Village dataset. The validation results underscored the potential of CNNs and presented a path toward AI-based deep learning solutions for disease detection, achieving an accuracy of 94.6%.

TABLE III
PLANT DISEASE DETECTION USING IP AND ML

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[123]	2019	120 images of three diseases, Brown spot, Leaf smut and Bacterial leaf blight. 420 images after augmentation.	Correlation Attribute Eval technique	Logistic Regression, KNN, Decision Tree (J48), and Naive Bayes.	LR- 70.83% KNN- 91.6%, DT- 97.91% NB - 50%
[124]	2020	14956 images of different 38 classes.	Texture Features, Color Moments Features, Gobor Wavelet Transform Feature, Shape Features, Zernike Moment Features and Vein Features.	Random Forest, Support Vector Machine, K-Nearest Neighbor, and Artificial Neural Network.	RF- 73.38% SVM-67.27% ANN- 65.68% KNN- 63.20%
[125]	2021	PlantVillage	HSV color space and grey level co-occurrence matrix (GLCM)	Random Forest	Average accuracy of 93% is achieved.
[126]	2022	Village database of tomato leaf	Principal Component Analysis, Discrete Wavelet Transform, and GLCM	SVM, K-NN and CNN	SVM - 88%, KNN - 97%, and CNN - 99.6%
[127]	2022	120 images of three diseases, Brown spot, Leaf smut, and leaf blight.	Principal Component Analysis	RBF-SVM, SVM, Random Forest, and ID3	100% accuracy was achieved by RBF-SVM.
[128]	2022	Grape leaf dataset	Principal Component Analysis	SVM, PSO SVM, BPNN, and random forest algorithms.	PSO SVM achieved an accuracy of 97.5% of accuracy.
[129]	2023	122 images of rice, 2000 images of pepper, 2300 images of potato, and 16,000 images of the apple.	Colour features, Texture properties, and GLCM.	Linear Regression, Random forest-nearest neighbors, Support vector machine Naive Bayes and neural networks.	NB and RF achieved 97.5% of accuracy
[130]	2023	PlantVillage	Segmenting image features with Spatial Fuzzy C-Means	Hybrid Random Forest Multiclass SVM	98.98% of accuracy was achieved by the proposed model.
[131]	2023	Images of Robusta leaves	Greyscale co-occurrence matrix (GLCM)	Boosted Support Vector Machine-based Arithmetic Optimization Algorithm (BSVM-AOA).	98.6% of accuracy was achieved.
[132]	2023	Two rice datasets, DS1 and DS2	Color, texture and shape	Support Vector Machine (SVM) and Least Square SVM (LS-SVM)	91% for DS1 and 98.85% for DS2

In a different study, Bedi and Gole proposed a novel hybrid model combining Convolutional Neural Networks (CNN) and Convolutional Autoencoder (CAE) networks to identify the presence of Bacterial Spot disease in peach plants based on leaf images [140]. They utilized images from the Plant Village dataset. Their hybrid model first created compressed domain representations of leaf images using the encoder network of CAE and then performed classification using CNN. The model demonstrated impressive training and testing accuracies of 99.35% and 98.38%, respectively.

Furthermore, Tiwari et al. introduced a deep learning-based method centered on dense convolutional neural network (CNN) architectures for classifying and detecting plant diseases from leaf images captured at various resolutions [141]. They compiled a diverse dataset using images from four different databases, including the PlantVillage dataset, the iBean leaf image dataset, a dataset containing citrus leaf images, and another dataset containing rice leaf images from various regions worldwide. The presented dense CNN model achieved an average cross-validation accuracy of 99.58% and an average testing accuracy of 99.199%. These findings highlight the potential of deep learning in global disease detection efforts.

For the detection of viral infection at various parts of plants, Joshi et al. proposed three detection models VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3, based on CNN architecture [and were trained on an image dataset of Vigna Mungo plant leaves [142]. After comprehensive testing of the technique, all the proposed models produced testing accuracy for VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 as 91.23%, 96.42%, and 97.40% on various leaf photos, respectively. Albattah et al. proposed a robust drone-based deep learning approach EfficientNetV2-B4, to solve the classification task of crop leaf diseases [143]. The average precision, recall, and accuracy values were 99.63%, 99.93%, and 99.99%, respectively when trained on the PlantVillage dataset.

Deep learning, specifically CNN architectures like VGG16, DenseNet, AlexNet, etc., has revolutionized plant disease diagnosis in precision farming. These models offer automated and precise detection of diseases in plants, eliminating the need for manual inspection. By leveraging their feature extraction capabilities, CNNs provide an efficient and reliable solution

TABLE IV
PLANT DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[136]	2018	12,673 samples from PlantVillage	Color, Segmented and Gray-Scale Features	CNN model based on LeNet architecture	99.32% of classification accuracy.
[137]	2019	54,305 samples from PlantVillage	Auto feature selection	9-layer dense Convolution Neural Network.	96.46% of test accuracy.
[111]	2020	200 images of 15 different plants. A total of 3000 images were used.	Auto feature selection by CNN.	CNN	88.80% of test accuracy.
[138]	2020	Self-created dataset, 100 leaf images for each infected with the disease.	Auto feature selection by CNN.	CNN and K-means Clustering	Training speed of CNN increased to 85% and accuracy of 95% was achieved.
[139]	2021	36148 samples from PlantVillage	Auto feature selection by CNN.	Faster R-CNN, R-CNN and SSD	94.6% of Validation accuracy.
[140]	2021	4457 samples from PlantVillage	Auto feature selection by CNN.	Hybrid model based on Convolutional Autoencoder (CAE) network and CNN.	99.35% of training accuracy and 98.38% of testing accuracy.
[141]	2021	Images were collected from the Plant Village dataset, iBean Leaf image dataset, citrus leaf images, and rice leaf images.	Auto feature selection by dense CNN	Dense Convolutional Neural Network.	Average cross-validation accuracy of 99.58% and an average testing accuracy of 99.199%.
[142]	2021	Self-created Vigna mungo dataset of 433 images	Auto feature selection by the CNN models	CNN models: VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3	VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 achieved testing accuracy of 91.234%, 96.429%, and 97.403% respectively.
[143]	2022	PlantVillage Kaggle and images from drone samples.	Auto feature selection by the CNN model	CNN model: EfficientNetV2-B4	Average precision, recall, and accuracy values of 99.63, 99.93, and 99.99%, were achieved.

for accurately identifying and classifying plant diseases based on visual symptoms. The relevant literature has been efficiently condensed and presented in Table V, offering a comprehensive compilation of crucial aspects in the field of plant disease detection. This table encapsulates fundamental elements, such as the diverse array of datasets employed, alongside the implementation of popular CNN architectures, including VGG16, DenseNet, AlexNet, etc.

Ferentinos presented specialized deep learning models, including VGG, AlexNet, Overfeat, GoogleLeNet, and AlexNetOWTBn [55]. A publicly accessible database of 87,848 photos that were captured in both real-world agriculture fields and laboratory settings was used to train the models. VGG convolutional neural networks achieved 99.53% testing accuracy.

Khan et al. introduced technique that encompasses two critical stages for the detection of infected regions: contrast enhancement and segmentation based on correlation coefficients [144]. To extract features related to selected diseases, they leveraged two deep pre-trained models, VGG16 and Caffe AlexNet. Additionally, they performed a genetic algorithm selection before applying a multi-class SVM for the final classification stage. The experiments were carried out using two publicly available datasets, PlantVillage and CASC-IFW, resulting in an impressive model accuracy of 98.60%.

Hu et al. proposed a low-shot learning method employing SVM as a feature extractor, conditional deep convolutional generative adversarial networks (C-DCGAN) for data augmentation, and VGG16 as a classifier for tea leaf disease detection [48]. The VGG16 model was trained using 4980 images across three disease classes, achieving an accuracy of 90%. These approaches showcase the effectiveness of combining various techniques to enhance disease detection and classification.

Jiang et al. introduced a novel deep learning approach, INAR-SSD, based on enhanced convolutional neural networks (CNNs) using GoogleNet Inception and Rainbow concatenation [145]. They created the apple leaf disease dataset (ALDD) through data augmentation and image annotation tools, comprising intricate images captured both in field and laboratory settings. The INAR-SSD model achieved a remarkable 78.80% mean Average Precision (mAP) at a high detection speed of 23.13 frames per second (FPS).

Radhakrishnan proposed an algorithm that utilized AlexNet as a feature extractor and SVM as a classifier [146]. Their experimental analysis involved 60,000 plant leaf images sourced from the PlantVillage dataset. By combining CNN with SVM, they achieved an impressive accuracy of 96.8% for the detection of paddy blast disease, outperforming SVM as a standalone classifier. These findings demonstrate the value of leveraging deep learning techniques in disease detection and classification.

Chakravarthy and Raman implemented ResNet and Xception networks for disease classification [147]. They utilized three different versions of YOLO (YOLOv3, YOLOv3-tiny, and YOLOv3-SPP) to extract features for detecting diseased portions of tomato leaves. The ResNet achieved a classification accuracy of 99.73%, while the Xception network performed slightly better at 99.95% due to its increased complexity.

Argüeso et al. introduced Few-Shot Learning (FSL) algorithms for classifying plant leaves using deep learning techniques and limited datasets [148]. They fine-tuned the Inception V3 network in the source domain, and FSL incorporated Siamese networks and the Triplet loss. The accuracy in the source domain reached 91.4%, and in the target domain, it achieved 94.0%.

Darwish et al. proposed a combination of two pre-trained convolutional neural networks (CNNs), VGG16 and VGG19, as an ensemble model [149]. They addressed the issues of optimizing hyperparameters and dealing with local minima using the swarm optimization (OLPSO) algorithm and an exponentially decaying learning rate (EDLR) scheme, respectively. They trained and tested the model with a dataset comprising 16,408 maize images, achieving an accuracy of 98.2%.

Huang et al. a denoising approach based on asymptotic non-local means (NLM) for the detection of peach diseases, employing a parallel convolutional neural network model and an ipso-optimized extreme learning machine (ELM) layer instead of a SoftMax layer [150]. They collected 30,659 peach images from orchard sites and the internet for training and testing the model, achieving a testing accuracy of 88.13%.

In another study, Sujata et al. compared machine learning algorithms and deep learning algorithms [151]. They used Random Forest (RF), Stochastic Gradient Descent (SGD), and Support Vector Machine (SVM) and compared their performances with VGG-16, VGG-19, and Inception v3. They trained the models with 609 citrus images. Among all the algorithms used, VGG-16 achieved the highest accuracy of 89.5%, followed by Inception V3 and VGG-19 with 89% and 87.4%, respectively.

Rangarajan et al. employed a pre-trained deep learning model VGG16 for feature extraction and Multi-class SVM for classification in the context of classifying five different diseases in aubergine (eggplant) [152]. The model achieved an accuracy of 94.3%. Furthermore, they developed a customized version of the VGG-16 model, implemented it on a smartphone, and tested it in a trial setting, achieving a classification accuracy of 91.3%. These studies highlight the effectiveness of various deep-learning and machine-learning approaches in plant disease detection and classification.

Wang et al. proposed a trilinear convolutional neural network architecture using bilinear pooling to offer a more succinct way of identifying crops and diseases and classifying them separately [153]. Three pre-trained models Inception v3, ResNeXt-101, and VGG-16 were used as base models. For the PlantDoc dataset, the proposed model T-CNN using ResNeXt-101 as the base model achieved an accuracy of 75.58% for disease classification and 84.11% for crop classification. The same model achieved 99.7% and 99.9% of accuracies for disease classification and crop classification respectively. For field plant disease recognition (FPDR), Gui et al. proposed an enhanced CNN model with ResNet- 50 and channel orthogonal constraint to improve feature discriminativeness [154]. The proposed model achieved an accuracy of 72.03% and 99.84% on the Field-PlantVillage and PlantVillage dataset respectively.

Albattah et al. proposed a novel architecture Custom CenterNet with the DenseNet-77 as a base model for the categorization and automated detection of plant diseases [155]. PlantVillage Kaggle database is used for experimental analysis. CenterNet classifier achieved 99.982% accuracy. Ashwinkumar et al. presented optimal mobile network-based convolutional neural network (OMNCNN) involving bilateral filtering (BF) based preprocessing [156]. The MobileNet model and EPO algorithm were applied as feature extraction techniques and a hyperparameter optimizer and ELM-based classifier were used to allocate proper class labels. The model acquired 98.9% accuracy on the tomato leaf dataset. Harakannanavar et al. used multiple descriptors like Grey Level Co-occurrence Matrix (GLCM), Principal Component Analysis (PCA), Discrete Wavelet Transform (DCT) for feature extraction and KNN, SVM, and CNN for the classification of diseased and non-diseased leaves [126]. The proposed model DWT+PCA+GLCM+CNN was tested on 600 images of tomato leaf collected from the PlantVillage dataset and achieved an accuracy of 99.09%. Seven pre-trained CNN models EfficentNet-B6VGG-16, MobileNetV3, ResNet-50, DenseNet-121, Inception-v3, and ShuffleNet-v2 were evaluated by Jiang et al. [157] for identifying wheat leaf diseases. Two datasets Field-based Wheat Diseases Images (FWDI) dataset (259 images of healthy leaves and 2384 images of diseased leaves) and the PlantVillage dataset were used for the evaluation process. Lightweight CNN models, MobileNetV3 and ShuffleNet-v2 exhibited less accuracy at 87% than Inception-v3, which had the best classification accuracy of 92.5%.

Dhar et al. presented a novel feature extraction method in which a deep convolutional feature extractor is a pre-trained DCNN model, Xception, VGG-16, and VGG-19 [158]. An ensemble method of machine learning algorithms, SVM, RF, XGBoost, KNN and LR was used for the classification task. The highest accuracy achieved by the ensemble model was 95.8% when V66-16 was used as a feature extractor followed by VGG-19 and Xception with 94.7% and 94.2% respectively. Koklu et al. used three different methods using MobileNetv2 and SVM to classify grapevine diseased leaves [159]. A fine-tuned MobileNetv2 was used for classification in the first method whereas in the second, Logit's layer of the MobileNetv2 model was used for extracting features and SVM core functions as a classifier. Third, the Chi-Square method was used to select extracted features and SVM as a classifier. The highest accuracy of 97.6% was achieved for the third method evaluated on a dataset of 500 images of grapevine with 5 different classes followed by first and second, 97.2% and 96.4% respectively. Tain et al. proposed three models, VGG-16, InceptionV3 and ResNet50 to identify tomato leaf diseases using three different datasets (Inhouse dataset, PlantVillage, and images collected from Internet) [160]. The presented models were trained on 61,616 images taken from three datasets and achieved an accuracy of 99%. Additionally, a mobile application named TomatoGuard was developed.

Thakur et al. proposed a lightweight Convolutional Neural Network, VGG-ICNN, and was trained on five different publicly available datasets [161]. The highest accuracy of 99.16% was achieved for the PlantVillage dataset. Aishwarya et al. proposed lightweight custom CNN model to detect tomato plant diseases [162]. The model was trained on tomato leaf images collected from the PlantVillage dataset and achieved an accuracy of 98.44%. He et al. proposed MFaster R-CNN based on the Faster R-CNN model for the detection of nine different diseases of Maize plants. The model was trained on maize leaves collected from the internet and field and achieved an average accuracy of 97.23%. He et al. presented MFaster R-CNN, an improved version of the Faster R-CNN algorithm, tailored for intelligent maize disease diagnosis in real field conditions with complex backgrounds and similar disease characteristics [163]. MFaster R-CNN outperformed Faster R-CNN and SSD in disease detection, achieving an overall accuracy rate of 97.23%. It also reduced detection time compared to both Faster R-CNN and SSD, offering a valuable tool for timely and accurate maize disease prevention and control in the field.

C. Transfer Learning

Plant disease detection is a challenging problem due to the vast number of plant species and the diverse range of diseases they can encounter. By utilizing transfer learning, researchers have taken advantage of the learned features and representations from the pre-trained models and have already been exposed to a vast array of object categories. One of the key advantages of transfer learning in plant disease detection is the ability to overcome the scarcity of labeled plant disease datasets. Collecting a large-scale dataset with diverse plant diseases and labeled samples is often laborious, time-consuming, and requires domain expertise, however, transfer learning has become a pivotal technique in plant disease detection, leveraging the strengths of pre-trained models to improve performance, mitigate data scarcity challenges, accelerate training, and enhance generalization capabilities. Table VI encompasses pivotal details, including the diverse range of datasets employed for experimentation, the multitude of transfer learning models harnessed, and the associated accuracy metrics.

Lepage et al. utilized GoogleNet based on transfer learning to identify the impact of dataset size for the classification of plant diseases [46]. For training and testing, 1383 images of 12 plant species with 56 classes were used and 87% accuracy was achieved. Coulibaly et al. proposed the method based on the extraction of features of a pre-trained CNN model, VGG-16 [164]. VGG-16 was trained in a limited dataset of 711 images of good health mildew diseases and achieved an accuracy of 95% and 91.75% F1 score. Shrivastava et al. used transfer learning-based pre-trained AlexNet model and SVM for feature extraction and for classification respectively [165] to classify rice leaf diseases. The model was evaluated on a rice dataset of 619 images and achieved an accuracy of 91.37%. Mukhti and Biswas evaluated four transfer learning on the dataset consisting of 38 different categories of plant images collected from GitHub [166]. ResNet50, VGG-16. VGG-19 and AlexNet achieved an accuracy of 99.8%, 94.9%, 91.7%, and 83.6% respectively. Sagar and Dheeba carried out a multi-class classification issue using five pre-trained CNN models based on transfer learning, DenseNet169, ResNet50, Inception V3, MobileNet and InceptionResNet [167]. Additionally, the authors added 4 convolutional and pooling layers, along with 2 dense layers. The models were evaluated using the PlantVillage dataset and ResNet 50 achieved the highest of 98.2 and F1 score of 94%.

Xiong et al. designed an Automatic Image Segmentation Algorithm (AISA) based on the GrabCut algorithm and transfer learning model MobileNet for the required classification of plant diseases [168]. The presented model was trained on a hybrid dataset of PlantVillage and field images and achieved an accuracy of 91%. Zhong and Zhao proposed DenseNet-121 for the identification of apple leaf diseases, with three different methods of multi-label classification, focus loss function, and regression [169]. These methods were evaluated using 2462 apple images of 6 different classes from the PlantVillage dataset. DenseNet-121 with multi-label classification, focus loss function, and regression achieved an accuracy of 93.31%, 93.51%, and 93.71% respectively. Atila et al. presented 8 models of EfficientNet (B0, B1, B2, B3, B4, B5, B6, B7) and compared them with four pre-trained models of CNN, AlexNet, ResNet50 VGG-16, and Inception V3 [170]. The models were trained on the PlantVillage dataset and augmented data. With augmented data, EfficientNetB5 achieved the highest accuracy of 99.97% and without augmentation, B4 achieved an accuracy of 99.91%. Hassan et al. implemented four pre-trained CNN models EfficientNetB0, InceptionV3, MobileNetV2, and InceptionResNetV2 with dept=separable convolution, reducing the number of parameters [171]. The model was trained and tested on the PlantVillage dataset and EfficientNetB0 achieved the highest accuracy of 99.56%. Abbas et al. employed a Conditional Generative Adversarial Network (C-GAN) to create synthetic tomato plant images for data augmentation [172]. They utilized the PlantVillage dataset to train and test the classifier model, DenseNet121. The accuracy achieved by their method in classifying tomato leaf images into 5 classes, 7 classes, and 10 classes was 99.51%, 98.65%, and 97.11%, respectively. This approach demonstrates the efficacy of data augmentation using generative adversarial networks in improving classification accuracy. Yan et al. introduced a deep transfer learning framework designed for cross-species plant disease diagnosis, specifically focusing on poorly correlated domains [173]. The authors employed a novel approach called Deep Mixed Subdomain Adaptation Network (DMSAN) that incorporates the Mix-up strategy and utilizes the LMMD non-adversarial loss, known for its effectiveness. The DMSAN framework was applied for remote knowledge transfer in the context of classifying three different stages of plant disease development. A subdomain alignment mechanism facilitated knowledge transfer from the mixed domain to the target domain, effectively capturing fine-grained information. X. Liu et. al., addressed the critical issue of plant disease diagnosis in agriculture through visual analysis [58]. The authors constructed a substantial plant disease dataset comprising 271 categories and 220,592 images, catering to the challenging nature of plant disease images with diverse symptoms and complex backgrounds. The proposed method emphasized diseased regions using patch weight computation based on cluster distribution, enabling effective disease recognition. In contrast to feature maps generated by conventional deep networks like VGG16 and ResNet152, the proposed reweighted maps exhibit a superior ability to encompass discriminative regions in plant disease images.

Paymode and Malode created a dataset consisting of 4449 real images of grape and tomato leaves. Transfer learning-based VGG-16 was used for data processing, testing, and training [174]. The model achieved

TABLE V
PLANT DISEASE DETECTION USING VARIOUS CNN ARCHITECTURES

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[55]	2018	Publicly accessible database of 87,848 images.	Auto feature selection by the models	VGG, AlexNet, Overfeat, GoogleLeNet, and AlexNe-tOWTBn	Testing accuracy of 99.48%, 99.06%, 98.96%, 97.27%, and 99.44% was achieved by VGG, AlexNet, Overfeat, GoogleLeNet, and AlexNetOWTBn respectively.
[144]	2018	plant village and CASC-IFW datasets	Correlation coefficient and deep features (CCDF)	VGG16, caffe AlexNet, SVM and GA.	98.60% of classification accuracy is achieved.
[48]	2019	ALDD dataset consisting of 2029 images corresponding to 5 classes.	Geometric features and auto feature selection by CNN-based model	CNN-based model INAR-SSD and VGG-INCEP	97.14 % of accuracy achieved by VGG-INCEP. INAR-SSD model provides a high-performance solution for early diagnosis of apple leaf diseases.
[145]	2019	4980 images of tea leaf	Color and Texture	SVM, C-DCGAN and VGG16	90% of accuracy.
[146]	2020	4281 tomato images collected from PlantVilage dataset	Auto feature selection by YOLO	ResNet and Xception	ResNet's achieved an accuracy of 99.735% and Xception 99.952%.
[147]	2020	60,000 images of Rice leaves from PlantVillage	Auto feature selection by AlexNet	AlexNet and SVM	96.8% of accuracy is achieved
[148]	2020	54,303 images from the PlantVillage dataset	Auto feature selection.	FSL, Siamese network, Inception v3 and SVM	Source domain achieved 91.4%, and the target domain achieved 94.0% of accuracy.
[149]	2020	Dataset consisting of 16408 maize leaf images	Auto feature selection.	Ensemble model of VGG16 and VGG19, swarm optimization (OLPSO) algorithm	98.2% of accuracy is achieved.
[150]	2020	30,659 peach pictures and 102,052 augmented peach images	Auto feature selection.	Fusion of parallel CNN and ELM	88.13% of testing accuracy. The algorithm can be used to detect fruit surface defects
[151]	2021	609 citrus images	Texture futures by SVM, RF, and SDG. Auto feature selection by VGG-16, VGG-19, and Inception V3.	SVM, RF, SDG, VGG-16, VGG-19 and Inception V3	RF- 76.8%, SGD- 86.5%, SVM- 87%, VGG-19- 87.4%, Inception-v3- 89%, VGG-16- 89.5%
[152]	2021	2815 eggplant images.	Auto feature selection by VGG-16	VGG-16 and multi-class SVM	94.3% of accuracy and 91.3% accuracy when implemented in smartphone.
[152]	2021	PlantDoc and PlantVillage	Discriminative features	Trilinear CNN using Inception v3, ResNeXt-101 and VGG-16.	75.58% for PlantDoc and 99.7% for PlantVillage.
[154]	2021	52,306 images collected from PlantVillage and 665 field images	Discriminative features	CNN with ResNet-50	72.03% for Field-PlantVillage and 99.84% for PlantVillage.
[155]	2022	PlantVillage	Auto feature selection.	Custom CenterNet with the DenseNet-77	99.98% of accuracy.
[156]	2022	5512 images of tomato leaf disease from PlantDoc	Auto feature selection	Optimal mobile network-based convolutional neural network	98.92% of accuracy
[126]	2022	600 images of tomato leaf from PlantVillage	Texture-based features like Entropy, Autocorrelation, Sum of squares, Variance, Dissimilarity, Homogeneity and Average, and color and shape	CNN, SVM, KNN	99.09% of accuracy
[157]	2022	PlantVillage and FWDI	Auto feature selection	EfficentNet-B6VGG-16, MobileNetV3, ResNet-50, DenseNet-121, Inception-v3 and ShuffleNet-v2	92.5% of accuracy achieved by Inception-v3
[158]	2022	5000 images with 10 different classes and deep convolutional features	Deep convolutional feature	the ensemble model (SVM, KNN, XGBoost, RF, and LR). VGG-16, VGG19 and Xception	Highest accuracy was 95.8%.
[159]	2022	500 images of grapevine and 2500 augmented images	Auto feature selection, 1000 deep features in the second experiment and 250 deep features in the third experiment	MobileNetv2 and SVM	Highest accuracy was 97.6%.
[160]	2023	61,616 images taken from three datasets, an In-house dataset, PlantVillage, and images from the Internet.	Auto feature selection	ResNet50. VGG-16, InceptionV3	99% of accuracy.
[161]	2023	PlantVillage, Maize dataset, Rice dataset, Apple dataset and Embrapa	Auto Feature selection	Lightweight CNN (VGG-ICNN)	PlantVillage – 99.16% Maize- 91.36% Rice- 96.67% Apple-94.24% Embrapa- 93.66%
[162]	2023	16012 images of Tomato images taken from PlantVillage	Auto Feature selection	Lightweight Custom CNN model	Accuracy- 98.44% Precision -98.69% Recall- 98.33%
[163]	2023	2139 Maize images were collected from the dataset website and field, and 17,112 augmented images.	Auto Feature selection	MFaster R-CNN	Average recall rate of 0.9719, F1-score of 0.9718, and the overall average accuracy rate of 97.23% was achieved.

an accuracy of 98.40% for grapes and 95.71% for tomatoes taking color, shape, and texture as features. Vallabhajosyula et al. proposed an ensemble modal of pre-trained CNN architectures, deep ensemble neural network

(DENN). DenseNet201, ResNet101, MobileNetV3, InceptionV3 and MobileNasNet were used for the ensemble model [175]. The Mobile NasNet + ResNet101 + DenseNet201, and InceptionV3+ResNet101+MobileNetV3 achieved an accuracy of 99.9%. DENN model had 100% accuracy in all the other aspects. Transfer learning models using four different networks, and feature fusion technique was proposed by Fan et al. [176]. The authors incorporated center-loss constraint to increase the ability of the fused feature to discriminate. DenseNet, VGG-16, VGG-19 and InceptionV3 were evaluated on three different datasets, Apple dataset 1, Apple dataset 2, and Coffee Leaf dataset. The highest classification accuracy of 91.28% was achieved by InceptionV3. Gautam et al. proposed a Convolutional Neural Networks-based Deep Learning model using transfer learning architectures, VGG-16, VGG-19, ResNet, InceptionV3, and SqueezeNet [177]. A dataset of 1500 paddy images with 4 different classes was formed using Mandley and Kaggle datasets. Semantic segmentation and DNN were used for the extraction of the region of interest and classification respectively. 96.4% accuracy was achieved by the proposed model.

Subramanian et al. employed four pre-trained CNN models Xception, InceptionV3, VGG-16, and ResNet50 with image augmentation and Bayesian optimization [178]. The models were evaluated on 18,888 images of maize leaf and were used as fine-tuners and classifiers. All the architectures achieved accuracy above 99% as a fine tuner, and above 95% of accuracy as a classifier except ResNet50 with 79.44% and 93.59% as a fine-tuner and classifier respectively. For the detection of sugarcane leaf disease, a quantum-behaved particle swarm optimization-based deep transfer learning (QBPSO-DTL) architecture was presented by Tamilvizhi et al. [179]. SqueezeNet was used for feature extraction and QBPSO-DTL for tuning the hypermeters of deep stacked autoencoder (DSAE) model used as a classifier. The proposed model acquired an accuracy of 97.5% on the sugarcane plant dataset consisting of 80 images. Liu and Zhang introduced a novel method called PiTLiD, which leverages a pre trained Inception-V3 convolutional neural network and transfer learning techniques to identify plant leaf diseases using limited phenotype data [180]. The authors conducted experiments on various datasets with small sample sizes and found that PiTLiD outperforms existing methods, showcasing its robustness. PiTLiD addressed the challenge of limited training data without the need for a large number of traditional CNN samples. The method achieved an impressive accuracy of 99.45% on pathological images and demonstrated robust performance on other small datasets.

Al-Gaashani et al. used three traditional machine learning algorithms, multinomial logistic regression (MLR), support vector machine (SVM), and random forest (RF) for the classification of diseased tomato leaves taken from PlantVillage dataset [181]. For feature extraction NASNetMobile and MobileNetV2 were utilized. 97%, 95.2%, and 90% of accuracy was achieved by ML, SVM, and RF respectively. Mimi et al. developed three architectures, MobileNetV2-based transfer learning, vanilla CNN model, and CNN-SVM hybrid model to detect diseases from the self-created dataset of 3804 images of strawberry leaves and Catharanthus roseus [182]. MobileNetV2 model achieved the highest testing accuracy of 97.35% followed by vanilla CNN with 95.77% and CNN-SVM with 93.12%. Singh et al. applied transfer learning for the classification of Bean leaf diseases [183]. The authors used NesNet, EfficientNetB6, and MobileNetV2 with three different optimizers, RMSprop, Adam, and Nadam. The evaluation was carried out on a dataset of bean leaves consisting of 1295 images taken from the field using a smartphone. EfficientNetB6 with Adam Optimizer achieved 91.74% of validation accuracy. MobileNetV2 achieved 91.73% and 91.72% accuracy with Nadam and RMSprop optimizers respectively. Saeed et al. presented two pre-trained CNN models, Inception ResNet V2 and Inception V3 with different dropout rates. 5225 images taken from PlantVillage and on-field images were used to evaluate the presented models [184]. The Inception V3 and Inception ResNet V2 models had the best performance with 99.22% accuracy at 50% and 15% dropout rates respectively.

D. Attention Mechanism

The attention mechanism has proven to be beneficial for plant disease detection by enhancing the performance and accuracy of the models. By incorporating attention into the detection system, the model can effectively highlight and focus on the most relevant regions within plant images that are indicative of disease presence. This selective attention helps to filter out irrelevant or non-discriminative regions, allowing the model to make more accurate predictions [185]. One of the primary advantages of the attention mechanism is its ability to handle complex and large-scale plant images. Plant diseases can manifest in various ways, such as discoloration, lesions, or specific patterns on leaves or stems. By leveraging attention, the model can identify and prioritize these disease-related regions, enabling better discrimination between healthy and diseased plants [186]. Table VII covers essential information, which includes a variety of datasets used for experimentation, the incorporation of attention mechanisms, and the corresponding accuracy metrics.

Cap et al. proposed LeafGAN with a self-attention mechanism and a novel LFLSeg for the detection of disease and segmentation respectively [187]. 216,000 images of cucumber leaf images were used for evaluation. The LeafGAN models, with an average accuracy of 78.7%, outperformed the other two classifiers, Baseline and CycleGAN. Karthik et al. integrated attention mechanism in the residual network of CNN to increase feature learning in tomato disease detection [188]. 120,000 images of tomato leaves from the PlantVillage dataset were used for training and validation. The proposed model achieved an accuracy of 98% on the validation set. Chen et al. introduced a both-channel Residual Attention Network model (B-ARNet) in ResNet50 to classify tomato leaf diseases [189]. Prior to the optimization of KSW entropy by the Artificial Bee Colony algorithm (ABCK), the Binary Wavelet Transform combined with Retinex (BWTR) was used to enhance the denoising of images. A classification accuracy of 88.43% of accuracy was achieved by training over 8,616 images of tomato leaves.

TABLE VI
PLANT DISEASE DETECTION USING TRANSFER LEARNING APPROACHES

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[54]	2018	1383 images of 12 plant species with 56 classes	Auto feature selection	GoogleNet	87% of accuracy.
[164]	2019	711 images of millet leaf	Auto feature selection	VGG-16	95% of accuracy and 91.75% of F1 score.
[165]	2019	619 rice diseased leaf images.	Auto feature selection	AlexNet and SVM	91.37% of accuracy.
[166]	2019	70295 training images and 17572 validation images of 38 different plants collected from GitHub	Auto feature selection	ResNet50, VGG-16. VGG-19 and AlexNet	ResNet50-99.8%, VGG-16- 94.9%, VGG-19- 91.7% and AlexNet- 83.6%
[167]	2020	PlantVillage	Auto feature selection	DenseNet169, ResNet50, Inception V3, MobileNet and InceptionResNet	DenseNet169- 97.4% ResNet50-98.2%, Inception V3- 97.1%, MobileNet- 97.1% and InceptionResNet- 97.8%
[168]	2020	Hybrid dataset of PlantVillage and 8,378 field images	Auto feature selection	MobileNet, DenseNet, Inception, ShuffNet	91% of accuracy
[169]	2020	2462 images of apple leaf	Auto feature selection	DensNet-121, With regression Multi-label classification Focus loss function.	93.51%, 93.31%, 93.71% of accuracies.
[170]	2021	PlantVillage dataset	Auto feature selection	EfficientNet (B0-B7), AlexNet, Inception, VGG-16, ResNet50.	Highest accuracy was achieved by EfficientNet-B4- 99.91% without augmentation and EfficientNetB5- with 99.97% with augmentation.
[171]	2021	PlantVillage	Auto feature selection	EfficientNetB0, InceptionV3, MobileNetV2 and InceptionResNetV2	EfficientNetB0- 99.56%, InceptionV3- 98.42% MobileNetV2- 97.02% and InceptionResNetV2- 99.11%.
[172]	2021	16102 tomato leaf images from PlantVillage and Synthetic Images generated from C-GAN.	Auto feature selection	C-GAN and DenseNet121	99.51% of accuracy on 5 classes.
[173]	2021	Cross-species plant disease severity data set (CSPDS)	Auto feature selection	Deep Mixed Subdomain Adaptation Network (DM-SAN)	An average accuracy of 96.81% was achieved by DMSAN
[58]	2021	PDD271 and PlantVillage	Auto feature selection	LSTM, VGG16, ResNet152	99.78% of test accuracy was achieved by ResNet152.
[174]	2022	4449 original images of grapes and tomatoes and 62,286 augmented images	Shape, color and texture	VGG-16	98.40% for grapes and 95.71% for tomatoes
[175]	2022	PlantVillage	Auto feature selection	Deep Ensemble Neural Network–DenseNet201, ResNet101, MobileNetV3, InceptionV3 and MobileNasNet	100% accuracy
[176]	2022	1685 images of coffee leaf dataset, 1821 images of apple dataset 1 and 404 images of apple dataset 2.	Fusion of Deep features and HOG feature	DenseNet, VGG-16, VGG-19 and InceptionV3	DenseNet-78.52% VGG-16 – 73.79% VGG-19 – 81.49% InceptionV3- 91.28%
[177]	2022	1500 paddy images from Kaggle and Mandley.	Auto feature selection	VGG-16, VGG-19, ResNet, InceptionV3, SqueezeNet and DNN	96.4% of accuracy
[178]	2022	18,888 maize leaf images	Auto feature selection	Xception, InceptionV3, VGG-16 and ResNet50	Xception -95.45%, InceptionV3- 96.9% VGG-16 – 95.04% and 93.59% for ResNet50
[179]	2022	80 images of sugarcane plant	Auto feature selection	Quantum behaved particle swarm optimization based deep transfer learning, deep stacked autoencoder (DSAE), SqueezeNet.	97.5% of accuracy.
[180]	2022	Apple disease Images from PlantVillage Dataset	Auto feature selection	PiTLiD	99.45% of accuracy
[181]	2023	1152 tomato leaf images collected from PlantVillage	Auto feature selection	NASNetMobile, MobileNetV2, SVM. MLR and RF.	MLR- 97% SVM- 95.2% RF- 90%
[182]	2023	2239 captured images and 1565 images from internet	Auto feature selection	MobileNetV2-based transfer learning, vanilla CNN model and CNN-SVM hybrid model	End-users can monitor their plants in real time using an Android application.
[183]	2023	1295 images of bean leaf	Auto feature selection	NesNet, EfficientNetB6 and MobileNetV2	91.74% achieved by EfficientNetB6
[184]	2023	5225 images collected from PlantVillage and on-filed images	Auto feature selection	Inception ResNet V2 and Inception V3	99.2% of accuracy.

Wang et al. proposed Coordination Attention EfficientNet (CA-ENet) incorporating EfficientNet-B4 network and depth-wise separable convolution [190] for the detection of apple diseases. The model achieved an accuracy of 98.92% on the Apple Leaf Disease Identification dataset. Zhao et al. proposed a SEV-NET network, embedding the spatial attention and improved channel within the residual block of ResNet [191]. SEV-Net demonstrated classification accuracies of 97.59% for multiple plant diseases and 95.37% for the severity classification of a single plant disease when trained on two datasets of tomatoes. Chen et al. used MobileNet-V2 with an attention mechanism to identify various rice plant diseases [192]. The model achieved an accuracy of 99.67% on the Plant Village dataset. Wang et al. proposed an attention-based depthwise separable neural network with Bayesian optimization (ADSNN-BO) model for the detection of rice plant diseases [193]. The model was trained on a dataset consisting of 2370 images of rice leaf and achieved a testing accuracy of 94.65%. Chen et al. proposed a novel method BLSNet for the detection of rice bacterial leaf streak (BSL) disease, integrated with attention mechanism and semantic segmentation [194]. The model achieved an average accuracy of 94% on the rice dataset collected from the field.

Zhao et al. proposed DTL-SE-ResNet50 integrated with ResNet50, SENet and dual transfer learning [195]. The model was used to identify diseases in various vegetables and was trained on the AI Challenger 2018 database and a self-built database and achieved an F1 score of 94.85%. Zhao et al. proposed a fusion model based on Inception and residual structure (RIC-NET) with an embedded convolutional block of attention mechanism (CBAM) [196]. The model was trained on corn, potato, and tomato leaf images taken from the PlantVillage dataset and achieved an accuracy of 98.44%, 99. 43% and 95.20% respectively. Bhujal et al. used lightweight convolutional neural networks with different attention models, convolutional block attention module (CBAM), self-attention module, squeeze-and-excitation module, and dual-attention module [197]. All the models were trained on the Tomato set of the PlantVillage database and the model with CBAM achieved the highest validation of 99.51% followed by self-attention and dual-attention module with 99.47%. Zeng et al. proposed a lightweight dense-scale network (LDSNet) with improved dense dilated convolution (IDDC) for corn leaf disease detection [198]. Coordinated attention scale fusion (CASF) and an adaptive symmetric cross-entropy (ASCE) were designed for the reduction of network parameters and enhanced model training. The proposed model was trained on the corn set of the PlantVillage dataset and achieved an accuracy of 95.4%.

Stephen et al. examined four pre-trained CNN models, ResNet34, ResNet50, and two with a Self-attention layer based on transfer learning, ResNet18, and ResNet34 to improve the process of feature selection [199]. These pre-trained models are trained and tested using a dataset of 3355 images of rice leaves. ResNet34 with the self-attention layer achieved the highest accuracy of 98.54%. Yang et al. proposed an rE-GoogLeNet convolutional neural network model with an Efficient channel attention (ECA) mechanism and was trained field images and images collected from the Kaggle website [200]. The model achieved an accuracy of 99.58% and an F1 score of 100%. Thai et al. proposed Formerleaf, a transformer-based model with two algorithms, Important Attention Pruning (LeIAP) and Sparse matrix-matrix multiplication (SPMM) [201]. Both the models were trained on the Cassava disease dataset, the model with the LeIAP optimization method achieved an F1 score of 97.3% and 95.3% with the SPMM method. Xu et al. proposed an integrated model RFE-CNN, consisting of a residual channel attention block (RCAB), a feedback block (FB), elliptic metric learning (EML), and a convolutional neural network (CNN) [202]. The model was trained and tested on four different publicly available datasets, along with the self-created dataset. The model achieved the highest accuracy 99.95% for the self-created dataset followed by the Plant Disease dataset with 99.93%.

E. Image Segmentation

Image segmentation has emerged as a pivotal technique in the arena of plant disease detection, providing a nuanced and detailed representation of affected areas in plant imagery. Through image segmentation, the finer details of plant images can be dissected, distinguishing between the diseased and healthy regions of a plant [187]. This precision-driven approach allows for a granular understanding of the extent and nature of plant diseases, which can manifest in subtle ways, such as minute spots, streaks, or irregularities on plant organs. By isolating these disease-specific features, image segmentation facilitates a more targeted analysis, equipping models to discern even the earliest signs of plant diseases. This capability is paramount, especially when dealing with large-scale and high-resolution plant images where disease manifestations can be easily overshadowed by the vast expanse of healthy tissue. Table VIII presents vital data, encompassing a range of experimental datasets, the utilization of segmentation techniques, and the corresponding accuracy metrics.

M.A. Rahman et. al., aimed to enhance the accuracy of plant disease classification, with a particular focus on tomato leaf diseases, specifically Bacterial Spot, Late Blight, and Septo-rial Spot [203]. The proposed methodology consisted of four key phases: image enhancement, segmentation, feature extraction, and classification and emphasized image segmentation and feature extraction, employing two techniques: RGB thresholding and morphological operations. The proposed method achieved an accuracy of 99.25% on the Plant Village database, providing a robust solution for the accurate detection of tomato leaf diseases.

Sharma et al. investigated the use of segmented and annotated images to train convolutional neural network (CNN) models for the purpose of disease classification in tomato plants taken from the PlantVillage dataset [72]. By comparing the performance of a CNN model trained with segmented images (S-CNN) to one trained with full images (F-CNN), the study revealed a remarkable increase in accuracy, from 42.3% to 98.6% on independent, previously unseen data. Additionally, 82% of the test dataset exhibited heightened self-classification when the S-CNN model was used, signifying its enhanced reliability.

Iqbal and Talukder addressed the need for early detection and classification of potato leaf diseases, specifically Early Blight (EB) and Late Blight (LB), to improve crop production [204]. The proposed approach combined image processing and machine learning to automatically identify and classify these diseases. The authors use image segmentation on a dataset of 450 images containing healthy and diseased potato leaves sourced from the Plant Village database. This method effectively enabled the automatic detection of potato leaf diseases by leveraging image segmentation to extract meaningful features. The segmentation process was based on creating masks using color information, HSV color space intensity, and brightness. By thresholding the HSV image to distinguish green (healthy) and brown (diseased) regions, the system successfully identified and classified the various leaf conditions.

TABLE VII

PLANT DISEASE DETECTION BASED ON ATTENTION MECHANISM

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[187]	2020	216000 images of cucumber leaves	Auto feature selection	Leaf GAN with self-attention and LFLSeg	78.7% of average classification accuracy.
[188]	2020	95999 images for training and 24001 for validation of tomato leaves taken from PlantVillage.	Auto feature selection	Residual CNN with an attention mechanism.	98% of accuracy.
[189]	2020	8616 tomato leaf images	Auto Feature Selection	Residual Attention Network, Artificial Bee Colony algorithm for KSW optimization, and Binary Wavelet Transform combined with Retinex.	88.% of accuracy
[190]	2021	87,100 images of Apple Leaf Disease Identification dataset	Auto feature selection	Coordination Attention EfficientNet (CA-ENet)	98.92% of accuracy.
[191]	2021	Two datasets containing tomato leaf images, one set containing 26,749 samples and the other 13,308 samples.	Auto feature selection	SEV-Net	97.59% for multiple classes and 95.37% for single classes.
[192]	2021	Rice images collected from the PlantVillage dataset and locally formulated dataset of 200 rice plant images	Auto feature selection	MobileNet-V2 with an attention mechanism	99.67% of accuracy.
[193]	2021	2370 images of Rice leaf samples.	Visualization, heat-map, and silence-map	Attention-based depth-wise separable neural network with Bayesian optimization (ADSNN-BO)	94.65% of test accuracy.
[194]	2021	109 rice leaf images.	Auto feature selection	BLSNet with attention mechanism and semantic segmentation	94% of average accuracy.
[195]	2022	AI Challenger 2018 database and a self-built database	Auto feature selection	DTL-SE-ResNet50 integrated with ResNet50, SENet and dual transfer learning	F1 score – 94.85% Precision – 97.24% Recall- 92.58%
[196]	2022	3852 images of corn, 2152 images of potato, and 18,160 images of tomato leaf taken from the PlantVillage dataset	Auto feature selection	Fusion of Inception and residual structure (RIC-NET) embedded with a convolutional block of attention mechanism (CBAM) model	Accuracy Corn – 98.44%, Potato- 99.43% Tomato - 95.20%
[197]	2022	Tomato set of PlantVillage dataset	Auto feature selection	Lightweight convolutional neural networks with convolutional block attention module (CBAM), self-attention module, squeeze-and-excitation module, and dual-attention module.	Validation Accuracy of the model with CBAM – 99.51% Self-attention – 99.47% squeeze-and-excitation module – 99.05% dual-attention module- 99.47%
[198]	2022	Corn set of PlantVillage dataset	Auto feature selection	Lightweight dense-scale network (LDSNet) with improved dense dilated convolution (IDDC)	Accuracy – 95.4% F1 score- 95.4%
[199]	2023	3355 rice leaves images	Auto feature selection	ResNet34, ResNet50, Self-attention-based ResNet18 and self -attention based ResNet34.	ResNet34 with self-attention layer achieved 98.54%.
[200]	2023	36 images of rice leaf diseases collected from the field and 1086 rice disease images collected from the Kaggle website	Auto feature selection	rE-GoogLeNet	Accuracy – 98.58% F1 score- 100%
[201]	2023	Cassava Disease Dataset	Auto feature selection	Transformer-based model, namely Former Leaf with Important Attention Pruning (LeIAP) and Sparse matrix-matrix multiplication (SPMM).	LeIAP - F1 score of 97.3% SPMM – F1 score of 95.3%
[202]	2023	Plant Diseases, CGIAR, Plant Pathology, LWDCD 2020, and Self-created dataset with 7,329 wheat leaf images	Auto feature selection	Integrated deep learning model, RFE-CNN	Accuracy achieved by Plant Diseases dataset – 99.93%, CGIAR- 99.79%, Plant Pathology- 98.87%, LWDCD 2020- 98.98%, and Self-created dataset- 99.97%

Mukhopadhyay et al. introduced an innovative approach for the automatic detection of diseases in tea leaves, leveraging image processing technology and computationally intelligent algorithms [205]. The methodology combined the Non-dominated Sorting Genetic Algorithm (NSGA-II) for image clustering to identify disease areas in tea leaves, Principal Component Analysis (PCA) for feature reduction, and a multi-class Support Vector Machine (SVM) for disease identification. The proposed model is based on a real database that includes early-stage images of unhealthy tea leaves, aiding in the early detection and containment of diseases. Validation techniques, Correlation matrix analysis, K-Fold validation, under-fit/over-fit validation Tick/Cross comparisons, and comparisons with K-Means clustering support the effectiveness of the NSGA-II-based algorithm for image clustering.

Tassis et al. focused on automating the diagnosis of pests and diseases in coffee crops using deep learning methods [206]. The proposed framework integrated multiple convolutional neural networks (CNNs) to address instance segmentation, semantic segmentation, and classification. Mask R-CNN achieved 73.90% precision and 71.90% recall for instance segmentation, while UNet and PSPNet attain a mean intersection over the union of 94.25% and 93.54%, respectively, for semantic segmentation. The study addressed the complexities of disease and pest detection in coffee tree images due to factors like lighting and background variations.

Raj et al. proposed an approach that combined preprocessing and segmentation techniques using filtering and neural networks [207]. The dataset was constructed based on historical cultivation and disease-affected data, including live images from the fields. Initial preprocessing involved convoluted Gaussian filtering. A deep active contour convolutional neural network (DACCNN) was then used for image segmentation, creating novel loss functions that incorporate region and size information during training. The method detected and segmented primary plant leaf diseases such as Bacterial Blight, Cercospora Leaf Spot, Rust, and Powdery Mildew The system achieved a high accuracy of 98% in classifying the experimental results, using a benchmark dataset of healthy leaves and crop diseases.

Deb et al. addressed the challenging task of leaf segmentation in rosette plants, particularly when dealing with complex backgrounds and overlapping leaves in images [208]. The authors introduced a novel convolutional neural network, LS-Net, and evaluated its performance using datasets from plant phenotyping (CVPPP) [209] and KOMATSUNA [210]. LS-Net was compared to four existing CNN-based segmentation models, including Seg Net, Fast-FCN, and DeepLab V3, with U-Net and Pyramid Pooling Module. The experimental results clearly demonstrated the superiority of LS-Net in leaf segmentation, with an advantage in handling complex leaf images with light green backgrounds. LS-Net achieved high accuracy, with 97.36% and 98.92% test accuracies on merge and CVPPP datasets, respectively, as well as strong performance in terms of segmentation quality scores like dice and IoU.

Pal and Kumar presented the AgriDet framework for automated plant disease detection and severity classification [211]. It addressed the limitations of existing methods, including image constraints and background issues. The framework combined an INC-VGGN base network, Kohonen-based deep learning, and pre-processing steps for accurate disease detection and severity classification. Various computational intelligence techniques for image segmentation are used. However, limitations include the absence of real-world labeled datasets and challenges in detecting multiple diseases in a single image or repeated occurrences of the same disease. This framework holds promise for enhancing crop productivity by predicting and managing plant diseases.

Divyanth et al. addressed the need for precise disease management in corn crops by developing a two-stage deep learning-based approach for identifying and estimating the severity of Gray Leaf Spot (GLS), Northern Leaf Blight (NLB), and Northern Leaf Spot (NLS) diseases under challenging field conditions [212]. A custom dataset of field-acquired images was used for training three semantic segmentation models (SegNet, UNet, and DeepLabV3+). The UNet model excelled in stage one, extracting corn leaves from complex backgrounds with a mean weighted intersection over union (mwIoU) of 0.9422. In stage two, the DeepLabV3+ model successfully located, identified, and quantified disease lesions, achieving a mwIoU of 0.7379. By integrating these models, disease severity was accurately estimated, yielding an R2 value of 0.96 in the test set, signifying close alignment with actual observations.

Raggiolani et al. addressed the problem of jointly performing semantic, plant instance, and leaf instance segmentation in crop fields using RGB data for plant phenotyping [213]. The authors proposed a single convolutional neural network that handles all three tasks simultaneously, utilizing a hierarchical structure and introducing task-specific skip connections for improved performance. They also introduced a novel post-processing method to handle spatially close instances, a common issue in agriculture due to overlapping leaves. The network architecture was based on an ERFNet encoder and decoders for semantic and instance segmentation, and various loss functions are used to optimize different parts of the model. The proposed approach effectively tackled the challenges of plant instance and leaf instance segmentation while outperforming existing techniques.

In [214] Qadri et al. employed the Ultralytics YOLOv8 End-to-End model, trained with PlantVillage and PlantDoc datasets, to detect and segment plant leaf diseases swiftly and accurately. YOLOv8's advanced architecture allowed precise disease identification, and training it end-to-end enhanced its ability to generalize to new cases. The YOLOv8 approach was rigorously evaluated using metrics like precision, recall, mAP50, mAP50-95, and F1-score, yielding excellent results for both bounding box and segmentation mask tasks.

V. Challenges

Plant diseases have been a persistent problem in agriculture, causing significant yield losses and economic impacts. Machine learning and deep learning techniques are increasingly being explored as a promising solution for plant disease detection. However, implementing such systems presents numerous challenges that need to be addressed to ensure effective and reliable detection. These include issues related to data collection, model optimization, real-time processing, etc. Addressing these challenges is crucial for advancing the field of plant disease detection and enabling practical implementation in various agricultural settings. Various challenges are given below:

A. Datasets

Machine learning and deep learning techniques have broadened the horizons of plant disease detection. However, achieving an extensive and diverse dataset remains a challenging task due to several factors such as geographical location, weather conditions, and plant species. These factors lead to

TABLE VIII
PLANT DISEASE DETECTION BASED ON IMAGE SEGMENTATION

AUTHOR	YEAR	DATASET	FEATURES	MODEL	PERFORMANCE
[203]	2019	Tomato leaf dataset taken from PlantVilage	GLCM and gray-level histogram	DNN	99.25% of accuracy was achieved.
[72]	2020	Tomato plant images taken from PlantVilage and 731 images from the internet.	Auto feature selection	CNN	98.6% of accuracy was achieved.
[204]	2020	450 images of potato leaves	Hu moments, harlick texture, and color histogram	Several ML algorithms	Random Forest achieved an accuracy of 97% of accuracy.
[205]	2021	Tea leaf dataset	Variance, entropy, Inter-cluster distance, Skewness, and a number of cluster centres.	Multi-class SVM. PCA and NSGA-II, PCA.	An average accuracy of 83% was achieved by the proposed algorithm.
[206]	2021		Auto feature selection	ResNet, UNet, PSPNet and Mask- RCNN	Mask R-CNN achieved 73.90% precision and 71.90
[207]	2022	Self-created dataset and images taken from the field.	Auto feature selection	Deep active contour convolutional neural network	98% of accuracy achieved by the model.
[208]	2022	KOMATSUNA and CVPPP	Auto feature selection	LS-Net, Seg Net, Fast-FCN, and DeepLab V3, with U-Net and Pyramid Pooling Module	LS-Net achieved 97.36% and 98.92% test accuracies on merge and CVPPP datasets respectively.
[211]	2023	PlantDoc	Auto feature selection	AgriDet	54.3% of accuracy achieved by the proposed model
[212]	2023	Custom Corn dataset	Auto feature selection	SegNet, UNet, and DeepLabV3+	UNet achieved 0.9422 mean weighted intersection over union
[213]	2023	Sugar Beets dataset and GrowliFlower	Auto feature selection	ERFNet based decoder	IoU of 84.5 % achieved by the proposed method.
[214]	2023	PlantVillage and Plant-Doc	Auto feature selection	End-to-End YOLOv8	The assessment included precision, recall, mAP50, mAP50-95, and F1-score. The bounding box achieved 99.8%, 99.3%, 99.5%, 96.5%, and 0.999, while the segmentation mask scored 99.1%, 99.3%, 99.3%, 98.5%, and 0.992.

variations in disease symptoms and visual appearances that make it crucial to capture the entire spectrum of disease manifestations in the dataset [215]. Moreover, collecting a comprehensive and balanced dataset is not a trivial undertaking since some diseases are underrepresented compared to others leading to an imbalance in sample distribution across disease classes. This imbalance can adversely affect training models resulting in lower accuracy when detecting certain diseases. With this background information provided about plant disease detection using machine learning and deep learning techniques, three critical points come into focus: a) Acquiring an extensive and diverse dataset poses significant challenges; b) Variations exist within different types of plants depending on various environmental factors that need consideration while creating datasets; c) The imbalance in sample distribution across different categories leads to biased models exhibiting inaccuracies during model training.

B. Annotation Images

Annotating plant disease images for training machine learning and deep learning models is a daunting task that requires the utmost expertise in plant pathology to ensure accurate and consistent annotation of images with ground truth labels [216]. This process poses several challenges, primarily the need for specialized knowledge to identify various disease symptoms accurately. Domain experts such as plant pathologists are essential in guaranteeing the reliability of annotations due to their extensive experience in recognizing different diseases' symptoms and characteristics. Moreover, annotating a large-scale dataset can be time-consuming and resource-intensive, requiring substantial effort and domain expertise. The subjective nature of disease identification introduces ambiguity and inconsistency in the annotation process. Different experts may interpret symptoms differently leading to variations in annotations present significant hurdles towards achieving consistency in creating datasets with reliable ground truth labels [217]. Acquiring an annotated dataset that is comprehensive, accurate, and reliable becomes difficult because it demands considerable resources; this constitutes a significant challenge when developing effective detection models for plant diseases.

C. Integration of Deep Learning With Classical Segmentation Models

In the field of plant disease detection using computer vision and image analysis, there is a growing consensus that the performance of deep learning (DL)-based segmentation algorithms has reached a plateau. This challenge arises from the fact that, in certain application domains such as agriculture, DL models may struggle to deliver significant improvements in accuracy and reliability. To advance to the next level of performance in plant disease detection, researchers must consider the integration of CNN-based image segmentation models with traditional or "classical" model-based image segmentation methods. This integration is particularly challenging and essential for the following reasons:

1) Limited Dataset Availability: In the context of plant disease detection, obtaining large and diverse labeled datasets can be challenging. DL models often require massive amounts of annotated data to generalize well. Classical segmentation methods, on the other hand, may rely less on extensive data and can be effective with smaller, well-structured datasets.

Combining these approaches requires careful consideration of how to leverage limited plant disease datasets effectively.

2) Adaptation to Varying Conditions: Plant diseases manifest differently depending on factors like environmental conditions, plant species, and growth stages. Classical models, such as active contours or graph cuts, often require manual tuning of parameters to adapt to these variations. Integrating these models with CNNs in a way that automatically adjusts to changing conditions remains a challenge.

3) Real-Time Processing: In agricultural applications, real-time or near-real-time processing is critical for early disease detection and timely intervention. Deep learning models can be computationally intensive, and integrating them with classical models may pose challenges in achieving the required speed and responsiveness.

4) Interpretability and Explainability: Classical models like active contours and graph cuts offer a level of interpretability and explainability that DL models often lack. Researchers need to find a balance between leveraging the power of DL for feature extraction and combining it with classical models to provide interpretable results that can be trusted by domain experts.

5) Model Fusion Techniques: The integration of CNNs with graphical models, such as active contours or graph cuts, is a relatively recent and evolving area of research. Developing effective fusion techniques that harness the strengths of both approaches while mitigating their weaknesses is a complex task that requires further investigation.

6) Resource Constraints: In agriculture, resource constraints are common, including limitations in computational resources and power availability in remote field locations. Integrating DL with classical models should consider these resource constraints and aim for solutions that are efficient and scalable.

D. Generalization of Models

Developing accurate disease detection models across diverse plant species and environmental conditions is a complex process that requires careful consideration of numerous factors. One of the primary challenges in this area is the vast diversity of plant species, each with its unique characteristics and responses to stressors like diseases. In addition, environmental conditions can vary significantly from one location to another, making it challenging to develop universal models that work for all plants under all circumstances. There is a need for innovative approaches that go beyond visual inspection and consider genetic markers or other indicators specific to individual crops. Another challenge in developing accurate disease detection models is the lack of standardization in data collection methods [218]. Different researchers have different procedures when collecting data on plant health or symptoms, leading to inconsistencies between datasets and hindering efforts to develop reliable predictive models.

E. Real-Time Detection

Real-time plant disease detection systems are an essential tool for farmers to maintain crop health and increase yield [219]. However, these systems face significant challenges due to the computationally intensive deep learning models required for accurate detection, as well as limited resources in deployment environments. This arises due to the complexity of the algorithms and resource constraints present in deployment environments, hampering low-latency inference and processing large data volumes in real-time. The use of deep neural networks has proven successful in identifying the symptoms of diseases that occur on leaves or fruits by analyzing images captured with cameras. But training such models requires a large amount of data and computational power which can be difficult to achieve in practice. Furthermore, deploying such models on resource-constrained devices is challenging due to their high memory requirements and processing power.

F. Computational Resources

The use of deep learning models for plant disease detection on edge devices presents significant challenges due to resource constraints. Edge computing involves processing data closer to the source instead of relying solely on centralized cloud servers, which can lead to faster and more efficient analysis. However, this approach requires a tradeoff between computational performance and energy consumption. For example, deep learning models require large amounts of data and computation power, but edge devices are typically limited in terms of storage capacity and battery life. This becomes particularly critical when we consider deep learning-based plant disease detection systems. The need for real-time identification of plant diseases, whether in the field or greenhouse environments, demands that these models be able to operate quickly and with limited resources. It has shown that optimizing pruned models can reduce their size by up to 90% without significantly sacrificing accuracy [220]. This level of optimization not only allows for practical implementation on edge devices but also helps reduce energy consumption and associated costs. Despite the advantages offered by optimized models, there is still much work to be done in this area.

G. Transfer Learning

Transfer learning has emerged as a valuable technique in plant disease detection, enabling the adaptation of pre-trained models to new plant species or diseases, thus making the detection process more efficient and effective. By leveraging knowledge gained from previously learned data sets, transfer learning enables researchers to apply that knowledge to new datasets with minimal additional training required. However, despite its potential benefits, applying transfer learning can pose significant challenges due to differences between the pretraining dataset and the target domain. These differences can lead to suboptimal performance in detecting diseases. One major challenge is the domain shift that occurs when features learned from pretraining data fail to generalize well on target datasets with different characteristics.

VI. Conclusion

This paper provides a thorough review of the latest trends in plant disease detection, highlighting the importance of collecting data and using top-quality datasets to make models work better. Through honing data and image processing techniques, the refinement of data is improved, whereby segmentation methods pinpoint areas of interest and feature extraction amplifies classification accuracy. The study meticulously examined both conventional machine learning and emergent deep learning techniques within the classification context, underscoring the remarkable potential of convolutional neural networks (CNNs).

A comprehensive literature survey encapsulates the prevailing research status, offering a thorough analysis of pivotal papers that significantly propel the field's advancement. The escalating adoption of CNN methodologies not only manifests a transition towards more sophisticated and efficacious disease detection models but also casts light on concomitant challenges. Persistent issues, such as dataset diversity, model applicability, practical implementation, and interpretability, are substantial challenges that necessitate sustained scrutiny. Furthermore, it is imperative to acknowledge the potential deviations and anomalies in practical applications due to varied environmental and pathological conditions, which may impose additional complexities in model deployments and accuracy validations.

Additionally, these challenges underscore the indispensable need for multi-disciplinary collaborations and innovations, amalgamating expertise from both Plant Pathology and Computer Vision. Bridging the gap between these domains will potentially catalyze the development of more robust, efficient, and universally applicable plant disease detection mechanisms, thereby fostering a more sustainable and prolific agricultural sector. Future work may delve deeper into constructing hybrid models, harnessing both classical and deep learning algorithms, to achieve enhanced predictive accuracy and greater model interpretability, particularly under diverse and challenging field conditions.

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Syed Asif Ahmad Qadri (Member, IEEE) received the master’s degree in computer and information engineering (CIE) from International Islamic University Malaysia (IIUM). He is currently pursuing the Ph.D. degree with the Institute of Information Systems and Applications, Department of Electrical Engineering and Computer Science, National Tsing Hua University (NTHU), Hsinchu, Taiwan. His primary research interests include signal and image processing, computer vision, deep learning, machine learning, the AIoT, and smart agriculture.

Nen-Fu Huang (Senior Member, IEEE) received the Ph.D. degree in computer science from National Tsing Hua University (NTHU), Hsinchu, Taiwan, in 1986. He has been a Distinguished Professor with the Department of Computer Science, NTHU, since 2008. He has been the Dean of the College of Electrical Engineering and Computer Science, NTHU, since 2016. He is currently the Founder of ShareCourse, a MOOC platform in Taiwan. He has taught two celebrated MOOCs: Introduction to Computer Networks and Introduction to IoT, on ShareCourse, and more than 85 000 learners have enrolled in these courses. He has authored or coauthored more than 200 journal articles and conference papers, including more than 50 papers in IEEE INFOCOM/ICC/GLOBECOM flagship conferences. He has also granted or is pending more than 40 patents. His current research interests include the IoT networks and applications, MOOCs learning data analysis, network security, SDN/NFV networks, high-performance switches/routers, and network flow classification technologies.

Taiba Majid Wani received the master’s degree in communication engineering (CE) from International Islamic University Malaysia (IIUM). She is currently pursuing the Ph.D. degree with the Department of Computer, Automatic and Management Engineering, Sapienza University of Rome, Italy. Her primary research interests include multimedia forensics and computer vision.

Showkat Ahmad Bhat (Member, IEEE) received the Ph.D. degree in communication engineering from National Tsing Hua University (NTHU), Taiwan, in 2023. He is currently a Post-Doctoral Research Fellow with the Center of Innovative Incubator, NTHU. His primary research interests include edge computing, agriculture engineering, the IoT sensor networks, LPWAN (LoRaWAN/NB-IoT) transmission technologies and applications, blockchain technology, artificial intelligence, big data, and wireless sensor networks.