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Relevance of Advanced Plant Disease Detection Techniques in Disease and Pest Management for Ensuring Food Security and Their Implication: A Review

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Abstract

Plant diseases and pests present significant challenges to global food security, leading to substantial losses in agricultural productivity and threatening environmental sustainability. As the world's population grows, ensuring food availability becomes increasingly urgent. This review explores the significance of advanced plant disease detection techniques in disease and pest management for enhancing food security. Traditional plant disease detection methods often rely on visual inspection and are time-consuming and subjective. This leads to delayed interventions and ineffective control measures. However, recent advancements in remote sensing, imaging technologies, and molecular diagnostics offer powerful tools for early and precise disease detection. Big data analytics and machine learning play pivotal roles in analyzing vast and complex datasets, thus accurately identifying plant diseases and predicting disease occurrence and severity. We explore how prompt interventions employing advanced techniques enable more efficient disease control and concurrently minimize the environmental impact of conventional disease and pest management practices. Furthermore, we analyze and make future recommendations to improve the precision and sensitivity of current advanced detection techniques. We propose incorporating eco-evolutionary theories into research to enhance the understanding of pathogen spread in future climates and mitigate the risk of disease outbreaks. We highlight the need for a science-policy interface that works closely with scientists, policymakers, and relevant intergovernmental organizations to ensure coordination and collaboration among them, ultimately developing effective disease monitoring and management strategies needed for securing sustainable food production and environmental well-being.

Keywords

Disease Management, Detection Techniques, Advanced Detection, Sustainability, Science-Policy, Food Security

1. Introduction

The global population is projected to grow to around 9.6 billion by the year 2050 and continue increasing to 10.9 billion by the end of the century [1]. Given the current trends and projected population growth, an increase in food production by 60% - 70% is required for the global food supply to keep pace with the growing population [2]. While there is a demand for increased food production, pests and disease remain major challenges to global food productivity responsible for up to 20% - 40% of food loss while costing the global economy ~$220 billion [3]. The inability to provide interventions may lead to more loss, thus, several measures have to be taken to prevent 100% yield loss and exacerbate food insecurity [4] [5] [6] [7].

Many efforts have been made to prevent and control the disasters caused by pests and diseases. Traditionally, biological controls involve the use of predators of plant pests and the use of resistant crop varieties [8]. With the increase in invasive pests and more virulent pathogens, conventional methods are less effective, causing the otherwise resistant crop varieties to become susceptible [9]. The use of direct methods, such as molecular techniques, to detect plant pathogens has proven effective over the years as it has a high sensitivity, especially for microbes that may be present but visually undetectable, that is, symptomless. Molecular techniques also can be used instead of the traditional method of manually identifying pathogens by skilled taxonomists. Advanced detection and identification of pathogens are thus required to implement effective control measures to prevent greater yield loss [10] [11]. The methods of disease detection can be divided into two categories: direct and indirect, with the former performed in a lab setting while the latter is implemented *in site* and has limitations such as PCR when it comes to field sampling of diseases [12] [13]. Numerous potential methods have been overlooked, each with fewer risks and limitations, either due to slow time to yield results or a lack of details on effectiveness. This review aims to comprehensively examine plant disease detection techniques that encompass traditional and modern approaches. Additionally, the study delves into neglected methods that have the potential for success while offering strategies for improvement. The analysis will cover a wide range of techniques, including molecular techniques, immunological methods, remote sensing, high-throughput phenotyping, nanotechnology, and big data analytics. Moreover, the study will emphasize the importance of integrating disease and pest management strategies into detection methods. Key strategies to be highlighted include early detection, precision agriculture, targeted treatments, and integrated pest management. The study will also address the challenges and future directions in plant disease detection. It will underscore the necessity for continuous innovation, collaboration, and improvement to combat plant diseases and safeguard global food security effectively.

By expanding on these aspects and providing detailed discussions for each topic, the study will offer a comprehensive analysis of plant disease detection techniques. This will contribute to our understanding of effective disease management and support the development of strategies to ensure sustainable agriculture practices.

2. Traditional Plant Disease Detection Techniques

Primarily, the first step toward disease detection is by visually observing the symptoms present in the plants [14]. While this can provide some direction, the potential difficulty lies in effectively addressing the challenge. Visual observation does not provide any specific information about the microorganism causing the disease as well as the period of infection. Visual observation of plant symptoms has limitations in providing specific information about the causative agent and the stage of infection [15]. This method potentially leads to inaccuracies because it heavily relies on the expertise of the observer. Therefore, more advanced and standardized techniques for pathogen identification, detection, and quantification are necessary to overcome these limitations and ensure more precise and reliable disease diagnosis. Some of the previously used methods apart from visual observation of symptoms include microscopic evaluation of the morphological characteristics to identify pathogens, culturing on growth media, and serological, molecular, and phenotyping [16]. While some pathogens can be detected using a growth medium when applicable, multiple approaches can be utilized to determine the specific disease [14].

However, like any other approach, traditional methods also have their limitations and challenges. Time consumption, reliance on bulky machinery, and the need for expert personnel [17], as well as the detection of targeted and non-targeted pathogens [18], are some of the major challenges associated with these methods.

Addressing these challenges is essential to fully harness modern detection techniques and their potential for disease detection and management.

3. Overview of Advanced Techniques

Accurate and rapid identification of pathogens is essential in applying the most appropriate disease management to produce quality crops. Conventional methods used over the years to detect different plant pathogens may include; visual observation, microscopy, mycological assays, plant indicator tests, and more. However, plant disease diagnosis based on phenotypic features is not always reliable and has some limitations in time and accuracy. While some common plant diseases can be easily identified in the field with a trained eye, many symptoms displayed by unhealthy plants could also be due to environmental stress, poor soil conditions, insects and pests, chemical damage from fertilizers or fungicides, and even more than one pathogen can attack a plant. Also, some phytopathogens can cause disease with asymptomatic or weakly characteristic symptoms at the beginning of development [19]. Thus, the traditional forms of detection are at a disadvantage, as it becomes difficult to diagnose the diseases and identify their pathogens accurately. In the last two decades, with technological advancement came an improvement in rapid disease diagnosis techniques. Different phytopathogens, including fungi, bacteria, and viruses, can be identified using molecular and Immunological methods. These methods are highly effective for accurately identifying a pathogen at the species level. They provide real-time diagnosis, and the sensitivity of these analyses is much higher than that of conventional methods, which allows for the rapid and accurate detection of pathogens even in asymptomatic plants that may harbor relatively low pathogen populations.

3.1. Fluorescence *in Situ* Hybridization (FISH)

Fluorescence *in situ* hybridization (FISH) assays using oligonucleotide probes targeting rRNA were first introduced in 1969 [20] [21]. It examines the formation and detection of RNA-DNA or DNA-DNA nucleotide complementary hybrids in cells utilizing radioactively labeled oligonucleotides as probes [22]. FISH has since been used as a cultivation-independent tool to detect, identify, and quantify plant microorganisms [23]. It is a sensitive and robust method that recognizes plant pathogen-specific ribosomal RNA (rRNA) sequences. Thus, it provides a high affinity and specificity of DNA probes. These oligonucleotide probes are between 15 and 30 base pairs in length and are usually labeled with one or more fluorescent dyes [24]. This is important and useful to detect and target obligate biotrophs that are not culturable and allows for the direct study of plant pathogens in their natural environment [25] [26]. FISH technique is based on four core steps: 1) specimen fixation and immobilization; 2) permeabilization to increase the accessibility of an organism specific-nucleic acid probe to the target; 3) hybridization of the probe; 4) washing to remove unbound probe; and 5) documentation by microscopy or flow cytometry [27]. Although introduced many years ago, few studies have applied this technique to visualize oomycete plant pathogens such as *Phytophthora agathidicida* and *P. cinnamomi* [28] [29] [30]. Non-specific fluorescent staining techniques have been used to visualize infection structures, cellular plant growth, and response to the grape downy mildew pathogen *Plasmopara viticola* [31] [32] [33]. FISH assays have also been developed for species-specific visualization *of Plasmopara obducens*, an oomycete that causes downy mildew diseases in the ornamental bedding plant *Impatiens walleriana* [27].

3.2. Enzyme-Linked Immunosorbent Assay (ELISA)

ELISA is a serological technique introduced in the 1970s [34] and has since become the most widely used laboratory method for screening viruses in plant samples. Although ELISA was developed to study viruses that have characteristics that make early diagnosis challenging, this assay can also be used for detecting other plant pathogens, like bacteria and fungi [35] [36] [37]. Because of its high-throughput potential, ELISA can detect pathogens in plant propagation materials, including seeds, herbaceous cuttings, woody materials, rootstocks, and scions. In the enzyme-linked immunosorbent assay (ELISA), enzymatic reactions are used to detect and quantify the amount of a specific substance, such as viral proteins/particles in a sample. The antigens are the target epitopes from the viruses, bacteria, and fungi made to bind with antibodies conjugated to an enzyme specifically [38]. The detection can be visualized by spectrophotometry based on color changes resulting from the interaction between the substrate and the immobilized enzyme [39]. ELISA is sensitive, specific, inexpensive, and frequently preferred because of its speed and simplicity. However, the sensitivity of ELISA varies depending on the organism, sample freshness, and titer; for instance, bacteria can be detected at 100 $cfu \cdot mL^{-1}$ [40]. ELISA is also useful for handling large samples and can quickly provide quantitative and qualitative data [41]. Modifications of ELISA include; direct or double antibody sandwich (DAS) ELISA and indirect ELISA (I-ELISA). DAS-ELISA uses antiviral antibodies to trap viral antigens from plant samples by binding them onto a solid matrix to detect bound viral antigens [41]. On the other hand, I-ELISA has the advantages of achieving higher sensitivity in antigen detection and giving lower background absorbance values for healthy or nonhomologous samples [42].

3.3. Polymerase Chain Reaction (PCR)

Since the introduction of the polymerase chain reaction (PCR) technology for the development of monoclonal antibodies and amplification of nucleic acid sequences by Nobel laureate Kary Mullis in 1993, it has had a profound impact on plant disease diagnosis [12]. PCR was initially used to detect highly specific diseases caused by bacteria and viruses because of its high accuracy in DNA hybridization and replication [43]. PCR offers several advantages in detecting a single target in complex mixtures, rapid and specific detection of multiple targets, and the potential to detect unculturable pathogens. In PCR-based diagnostics, primers are designed to pair with unique DNA regions from target organisms for DNA amplification and detection. Specific amplification of target nucleic acid sequences is widely used to detect and identify plant pathogens [44]. In addition to the basic PCR technology, several variants have been developed over the years to increase the sensitivity of this technique. The reverse-transcription

PCR (RT-PCR) is used to amplify RNA targets due to its high sensitivity. It is an RNA-dependent DNA polymerase that catalyzes DNA synthesis using RNA as the template, thus is most practical for plant virus detection [45] [46]. While nested PCR (n-PCR) requires using one or two internal primers performed in two steps to amplify multiple sequences, multiplex PCR (M-PCR) enables the amplification of two or more target DNA or RNA sequences in a single reaction [47] [48] [49]. Multiplex nested RT-PCR was developed to increase sensitivity and specificity, especially when several pathogens frequently infect a single plant. Thus, it merges the advantages of M-PCR and nPCR in a single tube, reducing time and cost while allowing simultaneous detection of targets [50]. The major milestone in PCR utilization was the introduction of the concept of DNA amplification in real-time through fluorescence [51]. In real-time PCR, also called quantitative PCR (qPCR), the amount of DNA amplicons in the sample is measured after each cycle, reflected by the intensity of the fluorescent signal at that specific time. qPCR is a high throughput technique that achieves high speed, specificity, and reliability while overcoming cross-contaminations during sample handling after amplification. PCR depends on the efficacy of DNA extraction, and the performance is affected by inhibitors present in the sample assay, polymerase activity, PCR buffer, and concentration of deoxynucleoside triphosphate [52]. Even with some limitations, the invention of PCR has greatly boosted research in various areas of biology, including pathogen identification.

3.4. Loop-Mediated Isothermal Amplification (LAMP)

The LAMP (loop-mediated isothermal amplification) has been developed to be more easily applied in the field. This approach was first developed by [53] and was rapidly adopted for the detection of plant pathogens due to its speed, high specificity, sensitivity, efficiency, and isothermal conditions suitable for field conditions [54]. LAMP applies the strand displacement activity of Bst DNA polymerase (a polymerase enzyme) from *Bacillus stearothermophilus* [55] to amplify the target DNA through two or three pairs of specific primers in an isothermal condition. LAMP is a one-step amplification assay that amplifies the target DNA or RNA sequence and requires two or three pairs of primers to detect six distinct regions in the target sequence [56]. In many research articles, LAMP assays have been efficiently used to detect many pathogens, including fungi, bacteria, or viruses [57]. Also, LAMP was able to differentiate related fungal species that cause similar symptoms in plant and non-target strains of virulent species with lower detection limits. For example, on wheat plants, *Zymoseptoria tritici* and *Parastagonospora nodorum* often occur together and form the Septoria leaf blotch complex [54]. Innovations combining LAMP with other methods also promise to improve its effectiveness and usefulness. For instance, combining LAMP with a lateral flow dipstick (LFD) enables the assays to be more easily and widely applied for field diagnosis [58]. However, despite the advantages, limitations of the LAMP technique include a high risk of cross-contamination and subsequent false-positive results in controls because of its high efficiency in DNA amplification. Also, the target gene fragment is usually short, and the reaction products are a series of DNA fragments that are not the same size [54] [56].

3.5. Recombinase Polymerase Amplification (RPA)

Molecular techniques such as PCR and qPCR are widely used and have been demonstrated to be highly specific and efficient tools for diagnostics. However, the limitations of these methods include the need for a costly thermal cycler, stringent thermal cycling conditions, high-quality nucleic acids as a starting point, and a skilled operator, and they are relatively time-consuming. Next-generation sequencing involves high costs and requires complex data analysis. RT-LAMP needs a higher temperature for reaction conditions that are difficult and impractical in the field [59]. In recent years, alternative isothermal amplification, recombinase polymerase amplification (RPA), has become popular and made a new focus in nucleic acid detection due to its simplicity and accuracy. RPA targets the double-stranded DNA (dsDNA) by recombinase-primer complex and amplifies the target region through strand-displacement DNA synthesis [60]. Unlike the heat denaturation step in PCR (95˚C), RPA utilizes the *Escherichia coli* RecA (recombinase) and single-strand DNA binding protein (SSB) for DNA denaturation. It can successfully amplify targeted DNA sequences at 37˚C - 42˚C for 30 min with high sensitivity. The results can be visualized by combining them with fluorescence signals, lateral flow assay (LFA), or gel electrophoresis. RPA allows for the direct detection of DNA and RNA targets from crude plant extracts, equivalent sensitivity to molecular diagnostics such as PCR/RT-PCR, and no need for thermocycler equipment. Thus, RPA has the potential to be applied and implemented at on-site diagnostics, especially for unwanted plant diseases in farms, nurseries, and biosecurity, contributing to timely eradication measures and thereby minimizing the risk associated with the spread of the virus [61]. The application of RPA in plant pathology is expanding because of the attractive instrument simplification, portability, and cost-effectiveness. RPA does not require lab equipment in the field and can be easily used in small farms. RPA has been reported for the detection of several plant viruses, especially complex viruses that coinfect a particular plant. For example, an RPA assay was established to simultaneously detect maize chlorotic mottle virus (MCMV) and sugarcane mosaic virus (SCMV) that coinfect maize (**Figure 1**) [59]. Also, modifications to RPA described by [62] included a recombinase polymerase amplification (RPA)/Cas12a-based system that combines RPA and CRISPR/Cas12a for *Xanthomonas arboricola* pv. *pruni* (*Xap*) identification that causes Peach bacterial spot.

3.6. High-Throughput Phenotyping (Precision Agriculture) and Genotyping Techniques

Accurate and timely assessments of plant disease are important for plant disease management practices, plant breeding, and improving fungicide efficacy [63].

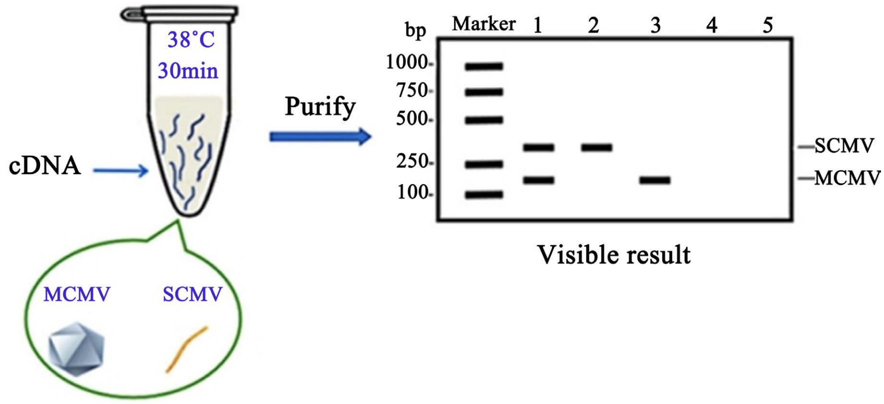

Figure 1. RPA assay for simultaneous detection of MCMV and SCMV [59].

These reliable assessments also help to forecast temporal and spatial disease spread in specific growing regions. While, Next-generation sequencing technology has greatly accelerated progress in pathogen detection and functional genomics [64] [65] [66], allowing quantitative trait locus (QTL) mapping and genome-wide association studies (GWAS) [67] to become powerful tools for elucidating the genetic architecture of complex traits [64] [68], and many genes governing important agronomic traits have been identified [69] [70]. However, phenotypic data acquisition is still a challenge restricting crop breeding and functional genomics studies [71]. Traditional crop phenotyping in the past decades has involved visual estimation, which has become more accurate and reliable due to detailed guidelines and standards used for assessment training [72] [73]. Nevertheless, visual estimation is always subjective to the rater's experience and can be affected by temporal variation. This variation causes significant interrater variability and changes in interrater repeatability [63] [73] [74]. These methods are also labor-intensive, time-consuming, and frequently destructive to plants [75] [76]. Therefore, acquiring high-throughput, effective, and comprehensive trait data needed to understand the genetic contribution to phenotypic variation has become an acute need [77] [78]. Plant phenomics has been defined as the high-throughput, accurate acquisition, and analysis of multi-dimensional phenotypes during crop growing stages at the organism level, including the cell, tissue, organ, individual plant, plot, and field levels [66] [79]. [80] also referred to plant phenotyping as the methodologies and protocols used to accurately measure plant growth, architecture, and composition at different scales. Intensive research has been done over the years to develop modern phenotypic tools that are sensor-based for plant disease detection, identification, and quantification [81] [82]. These sensors assess the optical properties of plants within different regions of the electromagnetic spectrum and are able to utilize information beyond the visible range (**Figure 2**) [63] [83]. They enable the detection of early changes in plant physiology due to biotic stresses because disease can cause modifications in tissue color, leaf shape, transpiration rate, canopy morphology, and plant density as well as variation in the interaction of solar radiation with

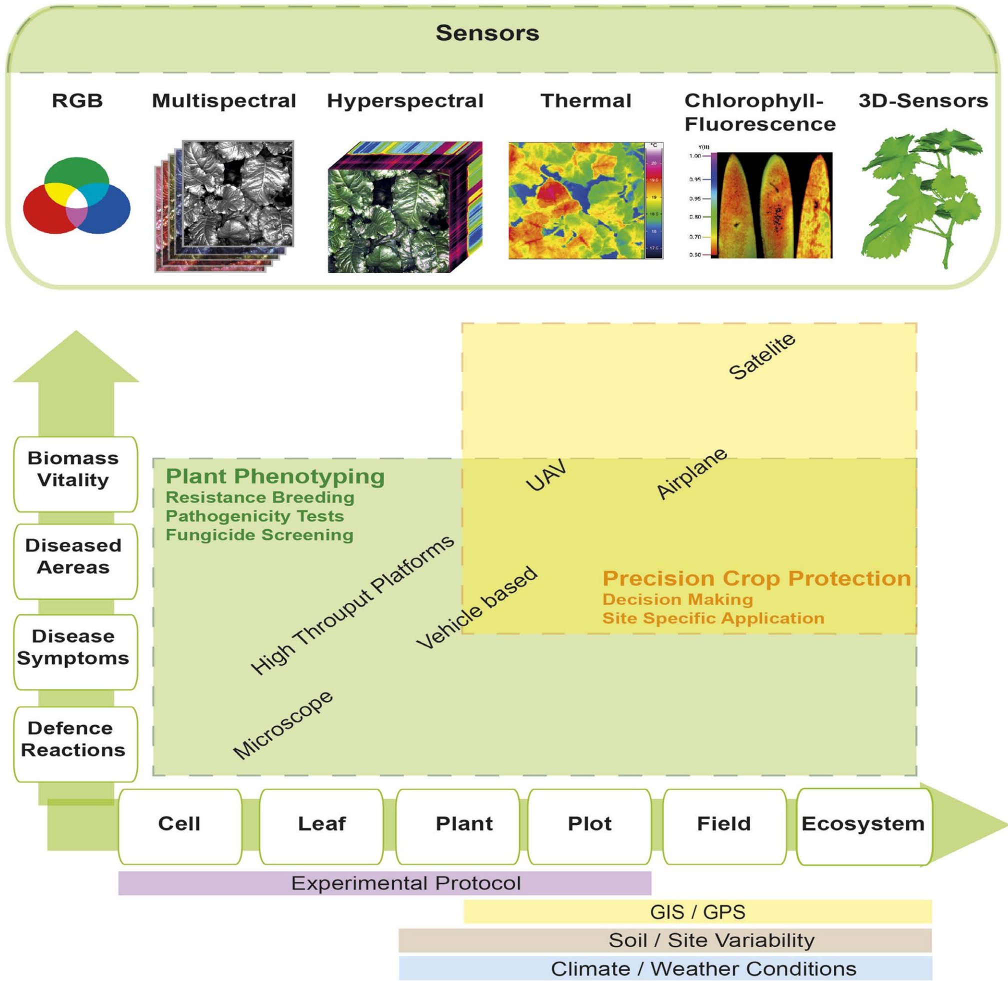

Figure 2. Overview of current sensor technologies used for the automated detection and identification of host-plant interactions [63] [83].

plants [84]. These modern phenomics tools aim at recording data on plant traits such as plant growth, biomass, architecture, and photosynthesis for hundreds to thousands of plants in a single day [17] [85], with increased precision and accuracy in phenotypic trait acquisition coupled with decreased labor input achieved by automation, remote control, and data (image) analysis pipelines [77] [78]. This shift has driven improvement in phenotyping technologies, which capture trait phenotypic data that can be linked to genomics information for crop improvement [86]. Thus, providing genetic information rapidly and promoting the development of large mapping populations and diversity of lines while phenotyping [87]. These tools also help identify important genes and evaluate new crop genotypes to improve photosynthesis [88]. For instance, high-throughput phenotyping platforms have been demonstrated to enhance GS in grain crops. For example, an unmanned aerial vehicle (UAV) carrying a remote-sensing unit with either an RGB or near-infrared, green, and blue (NIR-GB) camera has been used for the high-throughput phenotyping of sorghum plant height and different genomic prediction models [66] [89].

3.7. Remote Sensing (RS) and Imaging Technologies

Remote sensing means sensing things from a distance [90]. The "American Society for Photogrammetry and Remote Sensing (ASPRS)" defined remote sensing as "the art, science, and technology of obtaining reliable information about physical objects and the environment, through the process of recording, measuring and interpreting imagery and digital representations of energy patterns derived from non-contact sensor systems" [63]. Sensors may be classified according to the following:

1) The recording principle could be active sensors that emit radiation and measure the energy reflected (e.g. RADAR (radio detection and ranging), SAR (specific absorption rate), LIDAR (light detecting and ranging)) or passive sensors; measure reflected radiation (e.g. RGB, spectral cameras) [50].

2) The type of data recording could be imaging (e.g. RGB, spectral, thermal, fluorescence) or non-imaging (e.g. radiometers-spectroradiometers, fluorescence radiometers) [91].

3) The range of the electromagnetic spectrum could be visible (VIS; wavelength range, 400 - 700 nm), near-infrared (NIR; wavelength range, 700 - 1100 nm), short-wave infrared (SWIR; 1100 - 2500 nm), thermal infrared (TIR; 3 to 15 μm), and radar [92].

4) The scale/platform used, e.g. remote sensu stricto, airborne and space-borne, UAV (unmanned aerial vehicle), ground-based/proximal, and microscopic [50].

In the last decade, a number of RS systems have been developed, which are sensitive, consistent, standard, high throughput, rapid, and cost-effective [93], and can potentially be applied for detecting and monitoring plant diseases and pests. Few studies have applied active sensors such as SAR and Lidar remote sensing in monitoring plant diseases and pests, which might be due to the weak relationship between SAR and Lidar parameters and the symptoms of plant diseases and pests [94]. However, many efforts have been made to apply different RS systems in capturing the infection symptoms of pests and pathogens. The following describes the most relevantly used passive sensors.

3.7.1. RGB Cameras

Digital cameras are easy to handle and are a simple source of RGB (red, green, and blue) digital images for disease detection, identification, and quantification [63]. RGB sensors are in the visible or infrared bands [50]. RGB-color images have been used to detect biotic stress in plants [73]. However, the information from the three broad wavebands in the visible range is often insufficient for the differentiation of disease symptoms, but the combination with spatial information and the availability of advanced image processing methods makes RGB images a powerful tool in disease perception [91]. For example, several studies have used pattern recognition and machine learning tools to detect and identify plant diseases from RGB images [95] [96]. A plant disease database for automatic disease detection and identification that includes 2,326 images of 171 diseases and other disorders affecting 21 plant species was also established by [97].

3.7.2. Spectral Imaging Sensors

Multi- and hyperspectral reflectance sensors assess the spectral information of objects in the R, G, and B wavebands and in an additional near-infrared band [98]. While multispectral sensors produce broadband reflectance, hyperspectral provides spectral and spatial information for the imaged object in a narrow band [50] [63]. Hyperspectral data can be observed as huge matrices with spatial x- and y-axes and the spectral information as reflectance intensity per waveband in the third dimension, z. Thus, spatial resolution strongly influences the detection of plant diseases or plant-pathogen interactions [82]. The spectral signature of vegetation is influenced by biophysical and biochemical properties describing the canopy structure, such as leaf area index, the amount of life and senesced biomass, pigment and moisture content, and spatial arrangement of cells and structures [99] [100]. In healthy vegetation, reflectance occurs in the three distinguished spectral domains; however, in diseased and dead leaves, changes in reflectance result from modifications of biophysical and biochemical characteristics of plant tissue. Under stress, chlorophyll production may decrease, resulting in less absorption in blue and red bands in palisade cells. So along with the green band, red and blue bands are also reflected. Hence, yellow or brown color is developed in stressed vegetation [90]. Although differentiation between disease symptoms that may occur on a crop independently from each other or simultaneously is essential for these operational systems. However, many biotic and abiotic stresses can affect the same crop or plant product under the same conditions, and the cause of symptoms is not easily identified [101]. Thus, the uniqueness of spectral signatures of plant diseases is not universally agreed upon, as stress-causing agents and various pathogens often cause similar symptoms under spectral imaging systems. Nevertheless, spectral imaging is increasingly used for plant phenotyping and crop disease identification, especially in large-scale agriculture. Many such research studies are described in the review papers by [63] [90] [102] [103]

3.7.3. Thermal Imaging Sensors

Thermography allows imaging using the differences in surface temperature of plant leaves and canopies and is correlated with plant water status [104] [105], the microclimate in crop stands and changes in transpiration due to early infections by plant pathogens. Thermal sensors detect radiation emitted in the thermal infrared (8 to 14 μm) and display it in false-color images (**Figure 3**) [12] [103]. Thermal imaging may be applied on scales ranging from proximal ground-based equipment to airborne and spaceborne sensors [106] and is suitable for time-series measurements and monitoring purposes. This method has been very useful for many different operations of agriculture before and after harvesting, site-specific crop management, and precision farming [103]. Through analysis of thermal images, [107] successfully differentiated biotic (root rot) and abiotic (drought)

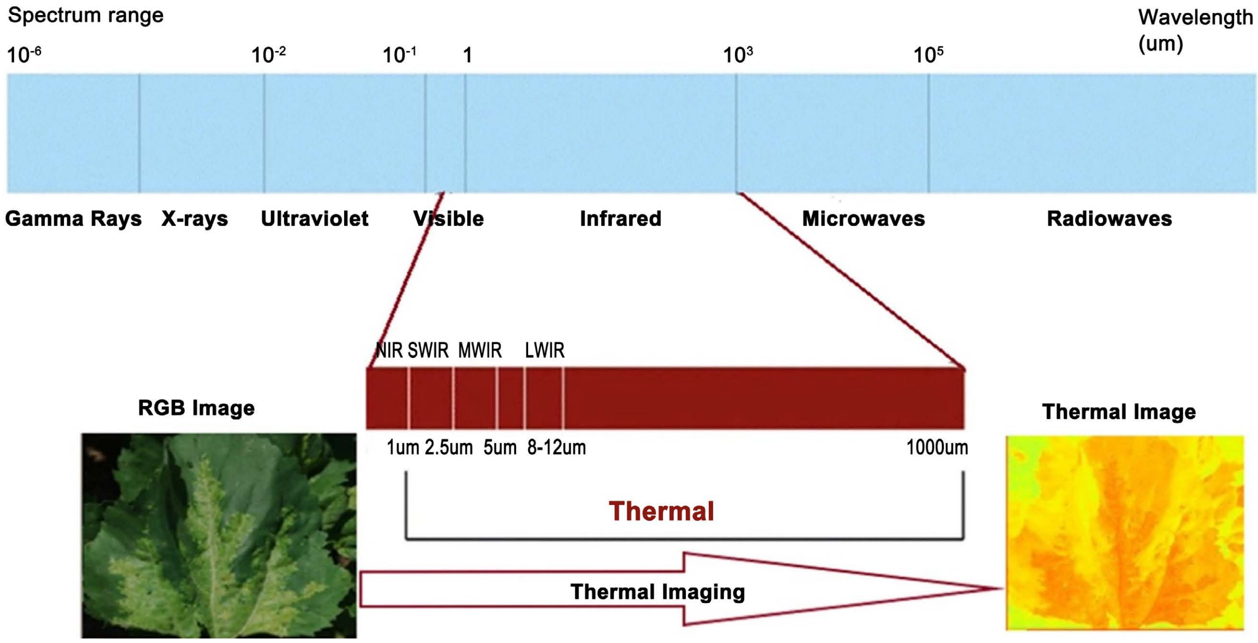

Figure 3. Description of thermal imaging radiation conversion [103].

stress in cotton. The potential of thermal techniques in the early detection of plant diseases and pests was also confirmed by some other studies [108] [109] [110]. However, the practical applicability of thermography for disease monitoring is limited due to its high sensitivity to changes in environmental conditions during measurements. Additionally, thermographic detection lacks specificity toward diseases and cannot be used to distinguish between diseases that produce similar thermographic patterns [12].

3.7.4. Fluorescence Imaging Sensors

Chlorophyll fluorescence assesses the photosystem II activity, which is highly sensitive to abiotic and biotic stress [111]. Pathogen attack affects the plant's photosynthetic apparatus, e.g. pigments, electron transport chain, and enzymes of the Calvin cycle, directly by reducing the photosynthetic leaf area (necrosis) and chlorophyll degradation (chlorosis) or indirectly through feedback regulation of the electron transport chain [112]. Thus, fluorescence RS systems measure the chlorophyll fluorescence on the leaves as a function of the incident light and the change in fluorescence parameters by tracking plants' respiration and photosynthetic processes, allowing for pre-symptomatic monitoring of plant diseases and pests [94]. Chlorophyll fluorescence's temporal and spatial variations were analyzed for precise detection of leaf rust and powdery mildew infections in wheat leaves at 470 nm [113]. In addition, Fluorescence spectra were useful in discriminating brown rust-infected tissue from healthy wheat tissue as early as four days after inoculation [114]. Although fluorescence measurement provides sensitive detection of abnormalities in photosynthesis, the practical application of this technique in a field setting is limited [115]. The patterns of disease symptoms on the leaf and plant level are often random and may be confused with effects due to arthropod damage [116].

3.7.5. Spectroscopy-Based Sensors

These are non-imaging sensors that often have a high spectral resolution (measuring hundreds of narrow wavebands separately) in the full range, but the spectral information results from the average of the sensor's field of view. These techniques hold particular promise for crop disease monitoring because of their potential as operational instruments, flexibility, efficacy, and cost-efficiency [50]. The most relevant and recent advances in spectroscopy-based techniques are VIS, IR spectroscopy, and Fluorescence spectroscopy. They are based on the inherent optical properties of leaf pigments, chemical components, properties, and structural characteristics [117]. Many studies have utilized these techniques for pathogen detection, as described by [50], and recently a study on the differentiation of winter wheat disease due to pathogens (yellow rust, powdery mildew) and insects (wheat aphid) infestation was recently carried out by [118].

3.8. Nanotechnology and Biosensors

The prevailing approach to pest management heavily relies on the utilization of pesticides, encompassing insecticides, fungicides, and herbicides. Despite their numerous merits, including wide accessibility, rapid efficacy, and dependability, pesticides exert detrimental effects on non-target organisms, contribute to the resurgence of pest populations, and foster the development of resistance [119]. Moreover, approximately 90% of applied pesticides are lost either during or after their application [120] [121]. Consequently, there exists a growing impetus to formulate cost-effective, environmentally friendly pesticides that demonstrate exceptional performance. The realm of nanotechnology has spearheaded the creation of innovative concepts and agricultural commodities, holding immense promise in addressing the aforementioned challenges. While nanotechnology has made significant strides in medicine and pharmacology, its application in agriculture has garnered relatively less attention [121] [122]. Nanotechnology encompasses the exploration and advancement of research and technology on the atomic, molecular, and macromolecular levels, enabling precise manipulation and examination of structures and devices within the range of 1 to 100 nanometers [123]. These entities operating within this scale are referred to as nanoparticles. Nanoparticles exhibit distinctive properties and functionalities that deviate significantly from those observed on a larger, bulk scale. Nanotechnology has also been used in various fields such as food packaging [124], and medicine [125], and can now be explored in disease management such as gene transfer, plant hormone delivery, water management, and pesticide absorption [126]. Although this novel application is relatively new in disease management, it can be explored for various disease diagnoses, monitoring, and projecting ahead of disease breakout. The integration of nanotechnology in agriculture is currently under exploration for a spectrum of applications, encompassing the delivery of plant hormones, facilitation of seed germination, optimization of water management, transfer of target genes, utilization of nano barcoding, deployment of nanosensors, controlled release of agrichemicals [126]. So, in plant disease management, Nanophytopathology is the use of nanotechnology to protect plants, detect diseases, and provide cures to the plants, thereby safeguarding the crops against widespread disease while ensuring effective crop protection [127]. Nano-sensors are a novel innovation that interacts with single DNA molecules to target diseases based on genome-targeted assays and are therefore useful because they can help target specific disease detection and probably control [127]. Nanoparticles can be employed in safeguarding plants through two distinct mechanisms: 1) nanoparticles themselves functioning as a safeguard for crops, or 2) nanoparticles serving as carriers for pre-existing pesticides or other active substances, such as double-stranded RNA (dsRNA). These nanoparticles can be administered via spray application or through drenching/soaking onto seeds, foliar tissue, or roots. When utilized as carriers, nanoparticles offer various advantages, including a) extension of shelf-life, b) enhancement of the solubility of pesticides with poor water solubility, c) mitigation of toxicity, and d) promotion of targeted uptake into the intended pest species [128]. Similar to nanoparticles in plant pathology is the use of Biosensors. Biosensors are highly specific biomolecular probes made up of enzymes and nucleic acids that target molecules with high accuracy. They have a broad range in numerous domains, such as surveillance of the pathologic process and discovery, pesticide residue surveillance, which may be effective in reducing the dangerous effect of the residue on man's health, improving food safety and quality assurance [129]. For example, [130] worked on using a wearable electrochemical biosensor to facilitate on-site analysis of organophosphorus pesticides (OPs) on crop surfaces.

Biosensors can also target specific plant hormones, such as water stressors [131] [132] thereby can be useful in the prevention of plant death during drought, protection of essential crops, and eventually the sustainability of the food systems contributing positively to the global economic development. Biosensors possess several advantages such as genetically encoded biosensors having the capability to swiftly identify fluctuations in the levels and dispersion of plant hormones within living cells [133], such that Regiart *et al.* introduced a microfluidic electrochemical immunosensor designed for the prompt identification of *Xanthomonas arboricola* within walnut plant samples [134]. This on-site diagnostic method demonstrated a threefold acceleration compared to ELISA and delivered notably enhanced specificity and sensitivity. However, they also have some challenges such as the difficulty involved in producing an integrated pesticide analysis for different grades and biosensor usage is labor intensive. There is ongoing research into timely identification approaches for this usage [15] [135].

3.9. Big Data Analytics and Machine Learning Applications

Visual examination is frequently used in traditional plant disease detection methods, which can be time-consuming and subjective. As a result, reactions are sometimes delayed, and control measures are ineffective. Recent years have seen the development of powerful tools for the early and precise detection of illnesses and pests, including remote sensing, imaging technology, and molecular diagnostics. Big data analytics and machine learning have completely changed many industries, including agriculture, by making it possible to analyze huge, complicated databases and derive insightful information. These technologies have shown tremendous potential for detecting plant diseases. [136] used deep learning algorithms to accurately identify and classify plant diseases in aerial photos taken by drones. Their method shortened the time needed to diagnose diseases and made early intervention and effective management techniques possible.

Moreover, the exploitation of big data in disease detection has been represented by the work of [137] who developed a disease prediction model based on multiple data sources, including environmental factors, crop phenology, and historical disease incidence. By integrating these assorted datasets and employing machine learning algorithms, they successfully predicted the occurrence and severity of diseases, facilitating targeted interventions and reducing crop losses. In addition to big data analytics, the integration of machine learning algorithms has enhanced disease detection and management. [138] developed a machine learning-based decision support system that analyzed real-time sensor data to accurately detect and identify plant diseases (**Figure 4**) [139]. Their system employed various machine learning techniques, such as support vector machines and random forests, to classify diseases based on symptom patterns, enabling timely and targeted interventions.

Due to developments in sensors, robotics, artificial intelligence (AI), and data interpretation, there are now exciting new options in automated and noninvasive plant disease diagnosis. A comprehensive examination of big data analytics

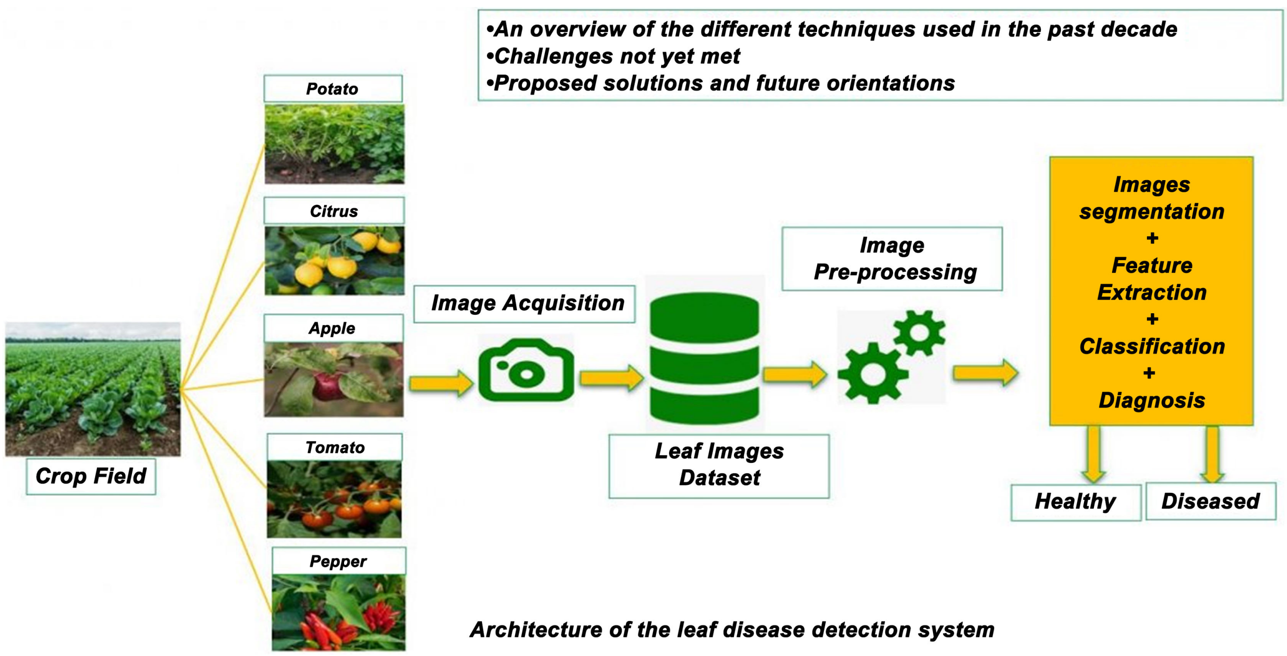

Figure 4. Illustration using artificial intelligence for crop disease detection [139].

and machine learning applications in plant disease diagnosis reveals several crucial factors. First, integrating automated plant disease diagnosis systems, leveraging the expertise of phytopathology experts along with deep learning convolutional neural network (CNN) algorithms, has shown promise in accurately identifying and classifying plant diseases and pests. However, the development of precise and efficient CNN models is crucial to ensuring reliable and rapid detection. Moreover, a comprehensive investigation is necessary to understand the various factors that impact the detection of plant illnesses. These factors include the availability and diversity of datasets, the learning pace of the algorithms, lighting conditions, and other relevant aspects. Thorough research in these areas is essential for optimizing the performance and effectiveness of disease detection systems [140]. Additionally, the integration of robotics technology at the field level necessitates a concerted focus on the interplay between artificial machine intelligence and natural human intelligence.

A critical assessment of big data analytics and machine learning applications in plant disease detection highlights the requirement for accuracy and speed in CNN models and detailed investigations into the factors impacting disease diagnosis. While robots and human intelligence interact to highlight the importance of continuous agriculture and plant protection research in the digital world, advances in artificial intelligence and machine learning also present intriguing future directions.

3.10. Hyperspectral Imaging and Artificial Intelligence in Plant Disease Detection

The dependable detection and identification of plant diseases and stress pose significant challenges in agriculture. Traditional methods of detection, relying on manual observation of visible indicator signs, are time-consuming, labor-intensive, and often limited to the late stages of infection [141]. Additionally, manual detection requires clear symptoms, which may not be evident in large crop areas or at the early stages of disease development. The identification of the causal agent typically involves manual detection or diagnostic tests, further adding to the complexity of the process.

To address these limitations, there is a growing interest in replacing manual processes with more automated, objective, and sensitive approaches. One promising avenue is the utilization of imaging sensors for plant disease detection. Various imaging techniques have been explored, including RGB, multispectral, hyperspectral, thermal, chlorophyll fluorescence, and 3D sensors (**Figure 5**) [142] [143]. Among these, RGB and hyperspectral imaging have shown a preference for identifying specific diseases [101].

Machine learning techniques and image analysis offer non-invasive and potentially autonomous approaches for detecting biotic and abiotic stress in plants. Researchers have explored high-throughput phenotyping, utilizing various sensors, to identify, classify, quantify, and predict stress. The use of machine learning algorithms allows for the analysis of large datasets and the extraction of

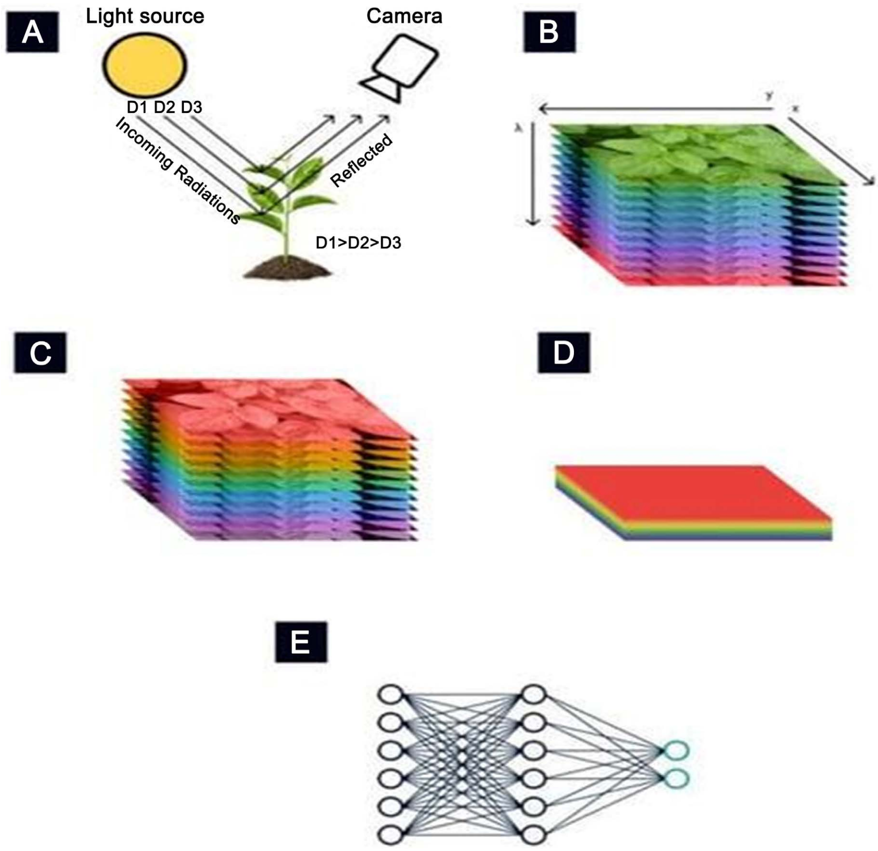

Figure 5. Hyperspectral data retrieval and processing remastered from (A) reflected light collection by the hyperspectral camera, (B) a hyperspectral data cube, (C) data normalization, (D) feature extraction, and (E) automation of the classification process [142] [143].

meaningful information from digital images. Hyperspectral imaging, in particular, has gained attention due to falling technology costs, making it more accessible to a wide range of users. This approach captures high-fidelity color reflectance information over a broad range of the light spectrum, beyond human vision. The ability to detect subtle changes in plant growth and development makes hyperspectral imaging promising for categorizing and recognizing the early stages of plant foliar disease and stress [10].

While hyperspectral imaging technologies are not yet provided as turnkey solutions for crop monitoring, advancements in this field and artificial intelligence techniques hold significant potential for revolutionizing plant disease detection. By providing accurate and early detection of diseases and stress, these technologies can contribute to improved crop management practices, targeted application of chemicals, and reduced environmental impact. However, further research and development are needed to refine and integrate hyperspectral imaging and artificial intelligence approaches into practical solutions for commercial deployment in agriculture. Therefore, the integration of sensors, robotics, artificial intelligence, and data interpretation has paved the way for automated and non-invasive detection of plant diseases. The use of deep learning CNN algorithms in automated plant disease diagnosis systems, combined with the expertise of phytopathology experts, has shown promise in accurately identifying and classifying plant diseases and pests.

4. Integration of Disease and Pest Management Strategies

Plants represent the primary source of food and nutrition for man and animals. However, plant diseases and pests cause significant damage to these crops, leading to reduced yields and poor quality of produce [5]. The annual crop yield loss caused by pathogens and pests is recently estimated at US$220 billion, directly impacting food security on a global scale [144]. This is even more crucial to prevent the devastating potential of emerging diseases or challenging pathogens that spread through asymptomatic individuals or hosts with subtle initial symptoms [145].

Therefore, early detection of plant pathogens along with quick, affordable, and accurate diagnostics is crucial for effective plant health monitoring and to arrest their spread at early stages of development [146]. For example, one of the world's deadliest plant pathogens, *Xyllela fastidiosa* subsp. pauca strain De Donno, destroys olive trees at an incredible rate, and unfortunately, it remains asymptomatic several months after initial infection, allowing the pathogen to spread unnoticed.

Given that traditional plant disease detection methods are laborious, time-consuming, error-prone, and generally inefficient, adopting advanced technologies such as remote sensing techniques, imaging technologies, machine learning and deep learning, and molecular diagnostics can be a powerful tool to overcome these shortcomings, allowing for early detection and prevention of plant diseases [83] [147]. Generally, the advantages of timely detection such as prompt intervention and reduced reliance on pesticides hinges substantially on early detection, and as a result fix many social, economic, environmental, and health problems [148].

Because of these limitations, effective disease and pest management strategies are required. Integrated pest management (IPM) is a promising approach that combines sustainable and holistic methods to combat crop pests and pathogens. This method suppresses pests and pathogens to economically insignificant levels [149] while addressing environmental concerns by combining biological and chemical controls [148].

Proactive measures such as early detection and monitoring play a crucial role in implementing timely interventions to prevent disease spread thereby reducing economic losses. Adopting sophisticated technologies such as remote sensing, imaging, and molecular diagnostics, for example, facilitates rapid, accurate, and cost-effective identification of diseases, including those in the early stages of development.

4.1. Precision Agriculture and Targeted Treatment

Precision agriculture (PA) techniques and targeted treatment are instrumental in optimizing plant health while minimizing the negative environmental impacts of disease and pest management practices. Infusing PA technologies such as advanced geoinformatics, computing and sensing infrastructure, and artificial intelligence into pest and disease control strategies would improve crop productivity and guarantee environmental sustainability through precise monitoring and forecasting of pests and diseases [148] [150]. For instance, in containing the devastating effects of late wilt disease (LWD) caused by *Magnaporthiopsis maydis* in maize, [151] deployed remote sensing to evaluate maize cultivars' resistance or sensitivity to LWD. This approach facilitated the simultaneous scanning and evaluation of a considerable number of plants, thereby enabling the early detection of symptomatic individuals and the identification of disease hotspots within the field [151].

Additionally, findings showed that integration of sensing drones equipped with infrared, thermal or audio sensors can effectively detect and identify damage caused by pests, as well as the presence of the pests themselves [148].

4.2. Integrated Pest Management (IPM) Approaches

An essential aspect of IPM is the incorporation of diverse methods and leveraging on their collective effects rather than relying solely on individual impacts [149]. IPM can be conceptualized as a multi-layered defense system. It begins with preventive measures, followed by biological controls, cultural practices, and physical barriers. Chemical control is used as a last resort if other actions fail to prevent pests from causing significant damage. Advanced disease detection techniques would improve the effectiveness of IPM approaches by providing accurate and timely information regarding pest presence and abundance. This helps farmers to make informed decisions on the best pest control measures to engage thereby minimizing their reliance on the use of broad-spectrum pesticides. Examples such as the USDA IPM program and California's wine industry demonstrate successful implementation of IPM strategies [152] [153]. These approaches effectively manage pests, minimize pesticide usage, and maintain crop quality.

4.3. Decision Support Systems for Disease Management

Decision support systems (DSS) are computer-based tools that help farmers and agronomists make informed decisions about managing diseases in crops, especially in complex and uncertain conditions [154]. Many DSS platforms in the USA are internet-based. They predict disease by utilizing weather data, crop information, and management data. Users input their field location, and the system retrieves their current weather data as well as the forecast data from the nearest station. Using this information, along with crop and management details, the DSS runs disease forecasting systems and a validated disease model to predict disease risks for various crops.

5. Implication for Food Security

Plant disease detection techniques have a significant impact on food security and offer a potential solution to reduce the negative impact of crop diseases on agricultural productivity. By improving disease detection, prevention and control, these technologies can help ensure stable food production and reduce yield losses caused by crop diseases.

5.1. Early Detection and Rapid Response

Advanced plant disease detection techniques enable early detection of diseases, enabling rapid response to prevent their spread. Remote sensing techniques such as hyperspectral imaging and thermal imaging can detect subtle changes in plant physiology and detect early stages of disease [63]. Early detection helps farmers implement targeted interventions, such as the use of pesticides and the removal of infected plants, to prevent the spread of disease and minimize crop losses [16]. [83] reported that techniques such as remote sensing, hyperspectral imaging, and unmanned aerial vehicles (UAVs) equipped with multispectral sensors enable early detection of disease symptoms. Similarly, satellite imagery and unmanned aerial vehicles (UAVs) combined with hyperspectral imaging and machine learning algorithms can detect subtle changes in crop health and identify potential disease outbreaks for immediate intervention and management [155]. Improvements in disease surveillance systems, such as geographic information systems (GIS), have enabled the creation of disease risk maps and early warning systems [145] [156], providing decision-makers with timely information on disease outbreaks, enabling targeted interventions and reducing the likelihood of infection and massive crop failure. Molecular techniques such as polymerase chain reaction (PCR), loop-mediated isothermal amplification (LAMP), and next-generation sequencing (NGS) are revolutionizing disease diagnostics [157], this could enable rapid and accurate disease detection. Plant disease detection integrated with data analytics and machine learning algorithms facilitates disease monitoring and forecasting. [158] reported that predictive models can predict disease outbreaks by analyzing historical disease data and environmental parameters, allowing farmers to take preventative measures. This approach improves the decision-making process and helps farmers optimize their disease control strategies.

5.2. Disease-Resistant Crop Development

Advanced techniques such as molecular markers and genomic selection are facilitating the development of disease-resistant plant cultivars. These techniques allow breeders to efficiently identify and select plants with desirable resistance traits [159]. By accelerating the breeding process, these techniques help produce improved varieties with increased resistance to disease, thereby reducing yield losses and increasing crop production. These techniques can help control emerging and re-emerging plant diseases, protect crop yields, and ensure food availability by improving the speed and accuracy of breeding. These strains have genetic traits that confer resistance or resistance to specific pathogens. By incorporating resistance genes, breeders can make plants more resistant to disease and reduce yield loss [160] [161]. [162] reported the use of genetically modified Bt cotton cultivars significantly reduced losses due to pest invasion. Disease-resistant crops can resist infection, reduce yield loss, and improve crop production.

5.3. Biosecurity and Global Trade

Rapid and accurate crop disease detection plays a key role in maintaining biosecurity and supporting global food trade. Early detection helps prevent the introduction and spread of new and exotic plant diseases across regions and countries [163]. This ensures the integrity of the food supply chain, avoids trade disruptions and protects the agricultural economies. International collaboration and knowledge sharing among researchers, policymakers and farmers can be facilitated. Platforms such as the Global Plant Health Information Network (GPHIN), the Digital Surveillance Network and the International Plant Protection Convention (IPPC) enable the exchange of information, best practices and early warning systems for controlling crop diseases at a global level. Such cooperation will strengthen global preparedness and collective responses to combat emerging crop diseases and ensure food security around the world. Improvements in crop disease detection systems also play an important role in adapting agriculture to climate change, as changes in climatic conditions can affect disease patterns. By integrating climate data and disease models, farmers and researchers can predict disease outbreaks, adapt cropping systems, implement proactive management strategies, and ultimately improve food security [164].

5.4. Environmental and Ethical Considerations

While these techniques described above offer promising solutions for controlling crop diseases and improving crop productivity, they also raise certain concerns and implications that need to be carefully considered. The use of genetically modified organisms (GMOs) and synthetic pesticides may raise concerns about unintended ecological consequences, such as the spread of transgenes into wild populations and the development of pest resistance. Increased use of synthetic pesticides can cause water pollution and damage to non-target organisms, which can impact the environment. The introduction of advanced disease detection technologies could impact smallholder farmers and developing countries. Access to advanced technologies and the resources needed to implement them such as genetically modified seeds and precision farming equipment are restricted and can be expensive. This could exacerbate existing inequalities in agricultural production and access to markets, potentially disadvantaging smallholder farmers and widening disparities between developed and developing regions. Furthermore, the development and use of these techniques raise ethical questions related to genetic engineering and biotechnology. Critics may argue that altering the genetic makeup of plants and introducing foreign genes into the food supply chain may have long-term health consequences that are not yet fully understood.

Additionally, its regulations can be complex, raising concerns about transparency, public engagement, and potential corporate control over farming systems. Biodiversity can be lost, making agricultural systems less resilient. Over-reliance on a limited number of genetically modified crops or uniform crop varieties can make food production more susceptible to disease outbreaks and environmental changes. Conserving diverse crop varieties and maintaining the resilience of agroecosystems is critical for long-term food security.

In summary, advanced crop disease detection techniques have far-reaching implications for food security. Early detection and rapid response, improved disease control, improved disease surveillance and sustainable crop production are key outcomes that help reduce crop losses and ensure a stable food supply. Timely interventions can reduce pesticide dependence and minimize the environmental impacts associated with excessive pesticide use. In addition, early disease detection and control measures help maintain crop productivity and quality, ensure food security, and reduce the economic burden on farmers.

6. Challenges and Future Directions

Incorporating advanced techniques for plant disease detection into disease and pest management strategies comes with both opportunities and challenges that need to be addressed for their successful implementation [165].

One major challenge in adopting advanced plant disease detection techniques is the limited availability and accessibility of necessary technology and infrastructure [137]. Implementing technologies like remote sensing and hyperspectral imaging comes at a high cost [166], coupled with the need for strong internet connectivity in rural areas, may hinder their widespread adoption among farmers and agronomists. Bridging this gap requires efforts to make these technologies more affordable, user-friendly, and accessible to smallholder farmers.

The persistent lack of integration of research programs has been a significant setback for decades, and this issue continues to prevail today [167]. The adoption of decision support systems for disease management has often been slow. This delay can be attributed to the unaddressed technical and perceptual limitations that arise during the development and implementation stages [168]. The growers' perceptions of risks and uncertainties associated with these techniques are also factors that contribute to the neglect of these valuable tools. Educating farmers and decision-makers about the benefits and effectiveness of these systems can help overcome skepticism and promote their adoption.

Although plant disease detection methods have come a long way, further exploration is needed to improve the precision and sensitivity of current methods. Research in machine learning should focus on pre-training networks to improve results, particularly in the field of plant disease detection [169] [170]. However, some techniques such as deep learning require a larger amount of data, and current datasets are often small and lack sufficient images for accurate decision-making. The lack of real-life situational images in available datasets and the inability to detect multiple diseases or occurrences of the same disease in a single image are also other aspects calling for improvement [171] [172]. Efforts should be directed towards creating larger, diverse datasets to enhance the accuracy and applicability of machine learning algorithms.

The invention of smartphone-integrated electronic readers and flexible sensors is causing exciting strides in plant disease detection [145]. These innovations allow for real-time plant monitoring and enable rapid in-flight assays. These advancements eliminate the need for time-consuming sample collection and analysis, thus enabling efficient emergency response and agricultural bio-surveillance. Embracing interdisciplinary approaches like climate-smart pest management (CSPM) can enhance food security by fostering collaboration and synergy among farmers, researchers, extension workers and stakeholders from the public and private sectors [173] [174]. This holistic approach bridges the gap between research and the agricultural community, thereby ensuring the effective implementation of disease management strategies.

In addition, the integration of recent advancements in wearable sensing, IoT technologies, and remote sensing techniques such as satellite imagery holds promise for effectively combating plant pathogens and pests [175]. This interconnected approach can provide real-time monitoring, precise disease detection and targeted interventions that contribute to more sustainable and efficient agricultural practices.

While these advanced techniques offer promising solutions for disease and pest management, it is imperative to consider their socioeconomic and environmental implications. It is crucial to evaluate the issues pertaining to affordability, fair access, and ethical concern associated with the use of genetically modified organisms and synthetic pesticides to ensure inclusive and sustainable agricultural practices.

In conclusion, addressing the challenges and exploring future research directions in plant disease detection will serve to bolster effective and sustainable disease and pest management strategies, which will ultimately enhance food security and ensure a stable food supply for a growing global population.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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