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Review

Crops Disease Detection, from Leaves to Field: What We Can Expect from Artificial Intelligence

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Abstract: Agriculture is dealing with numerous challenges of increasing production while decreasing the amount of chemicals and fertilizers used. The intensification of agricultural systems has been linked to the use of these inputs which nevertheless have negative consequences for the environment. With new technologies, and progress in precision agriculture associated with decision support systems for farmers, the objective is to optimize their use. This review focused on the progress made in utilizing machine learning and remote sensing to detect and identify crop diseases that may help farmers to (i) choose the right treatment, the most adapted to a particular disease, (ii) treat diseases at early stages of contamination, and (iii) maybe in the future treat only where it is necessary or economically profitable. The state of the art has shown significant progress in the detection and identification of disease at the leaf scale in most of the cultivated species, but less progress is done in the detection of diseases at the field scale where the environment is complex and applied only in some field crops.

Keywords: algorithm; crop; plant disease detection; study scale



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1. Introduction

The agriculture sector plays a crucial role in achieving the United Nations' goals of feeding the society by producing food to feed the growing population and providing livelihoods for millions of people [1,2]. Achieving these goals needs increasing crops yields by modern technologies but should encourage sustainable land use and practices to protect the environment, such as reducing chemical spraying.

1.1. Impact of Crop Diseases on Production and Agricultural Sector

Crop diseases have a significant impact on crop production [3]. Plant diseases are caused by pathogens such as viruses, bacteria, fungi, insects, and nematodes which may act alone or in combination, whose effect depends on the species or varieties encountered, the plant stage of development, the meteorological conditions [4], and the agroecological context [5,6] known as the disease triangle (plant–pathogen–environment) [7]. These different pathogens may cause significant reductions in crop yields, reduce the visual aesthetic aspect of the produce [8–10], alter the organoleptic quality, or produce toxic molecules [11–13]. The quantity or quality reduction generates direct losses for farmers with less amounts produced, or indirectly with products that cannot be sold (such as products presenting a visual damage), or not being able to sell at the highest price or having products that do not reach the normal standard size. Lastly, some pathogens produce toxic contaminants rendering the product inedible. This leads to economic losses for farmers which affect the food chain and at the end may generate a problem of food security for the population [14].

If farmers want to control pests, they will face increased costs as they spend more money on pesticides and other chemical treatments to control crop diseases, further reducing their profits [14]. Overuse of chemical treatments can lead to the development of resistance in pathogens, making it difficult or impossible to control crop diseases [15]. Furthermore, the overuse of phytochemicals may increase the risk of finding chemical residues on food, leading to food contamination and inducing a cumulative risk [16].

Lastly, farmers exposed to these chemical products may develop diseases themselves [17,18]. To mitigate the impact of crop diseases on production and the agricultural sector, it is important to implement effective disease management practices such as using disease-resistant varieties, crop rotation, and cultural practices that improve soil health, as well as Integrated Pest Management (IPM) techniques, which involve using a combination of methods such as biological, cultural, and chemical controls. Additionally, the research and development of new technologies such as genetic engineering and biotechnology can also help to develop disease-resistant crops.

1.2. Data Acquisition to Assess Crop Diseases

The rapid advancement of image and data collection is transforming how we assess crop disease. The reduced cost of unmanned aerial vehicles (UAVs) and the increased density of satellites have accelerated their use for agricultural purposes. Remote sensing with satellites and camera-equipped UAVs allows large-scale detection and mapping, enabling early intervention and targeted resource allocation to minimize yield loss [19–22]. If the data are either acquired on a large scale or with proximal tools like handheld camera supported by a stick, an armor, or ground vehicles, or just with a smartphone, the information collected will depend on the detector integrated. Those data could be image based or non-image-based approaches. Using imagery data has many advantages, including the ability to cover large areas quickly, the ability to detect diseases at an early stage, and the ability to monitor disease progression over time [23]. Early disease detection is crucial for effective disease management as it allows farmers to act before the disease spreads and generates a bigger yield loss [24,25]. Furthermore, the use of imagery data can also provide a more accurate assessment of disease incidence and severity, which can help in decision-making and resource allocation [24].

There are several image approaches using the following: RGB, multispectral, hyperspectral, thermal, and fluorescence imaging [26]. RGB imaging uses only the red, green, and blue wavelengths and has been used to detect disease presence in leaves but also in fruits [27,28]; multispectral imaging [21,29] uses a discontinuous but larger panel of wavelengths and hyperspectral [30] imaging uses a continuous and larger panel of wavelength. Both methods have been used for detecting diseases as they provide more information compared to RGB imaging. Lastly, fluorescence and thermal imaging provide complementary information to the three precedent ones as indicators of plant metabolism and biotic and abiotic stress [31,32]. Methodologies that are non-imaging based have also been developed to detect diseases in crops such as fluorescence, visible, and infra-red spectrometry [23,26,33,34].

Sensors and Internet of Things (IoT) devices are also used at the field scale to measure factors such as temperature, humidity, and light intensity that can affect disease development [35]. Data collected by these sensors can be used to predict disease risk and to trigger automatic responses such as applying pesticides [35,36].

1.3. Data Analysis to Detect and Identify Crop Diseases

Spectral data analysis, which examines light reflected from crops, plays a crucial role in early disease detection by identifying subtle changes in leaf color or texture [37]. These data, gathered from various sources, including ground-based sensors, aerial platforms, or satellites, allows for a comprehensive monitoring of diseases, often the first signs of disease. Machine learning algorithms analyze these image data to recognize patterns and track trends in disease development. This approach not only aids in current disease management

but also facilitates the prediction of future outbreaks and even builds models to optimize disease management strategies [38].

Using vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), which reflects plant health, further enhances the ability to monitor and predict crop health [39]. By employing these indices, researchers and farmers can develop advanced predictions and management strategies that respond dynamically to crop health needs [20]. However, implementing these methods requires significant expertise and resources, with each approach needing adaptation based on specific crops, diseases, and regional factors.

Machine learning (ML) and artificial intelligence (AI) techniques deployed to analyze data collected by remote sensors is providing new insights in the field of agronomy by its powerful learning algorithms [40]. ML and AI are deployed for different agronomical purposes such as patterns identification and trends in disease development, predicting disease risk, and to develop models that can be used to optimize disease management strategies [40,41]. Such technologies have applications across various agronomic needs, making them versatile tools for enhancing crop health and yield management [42].

Despite their benefits, it is important to note that the implementation of these technologies is not a one-size-fits-all solution. The selection and use of these tools must be tailored to suit the specific requirements of the crop, disease, and region involved [43]. Practical considerations, such as the costs of technology, the availability of trained personnel, and local infrastructure, are crucial to ensuring these technologies are used effectively.

Tools for assessing crop disease presence have many advantages and can be a valuable resource for farmers, researchers, and policymakers [19]. However, it is important to note that these methods should be complemented with other information, such as weather data, ground-based sensor data, and agronomic knowledge, to create a more comprehensive view of crop health, disease progression, and treatment needs. Additionally, an awareness of potential dataset limitations and biases in analytical methods is essential to achieving accurate, reliable outcomes in disease detection and management.

The main goal of this review is to assess recent advancements in detecting and identifying crop diseases through remote sensing and machine learning, spanning from leaf-scale to field-scale, the various data collection vectors, data processing techniques, and exploring practical applications for optimizing chemical use by enabling targeted treatment only where necessary.

2. Methodology

2.1. Crop Disease Detection Systematic Search Approach (SSA)

To gain a comprehensive understanding of the current research directions and to identify potential gaps in our knowledge, a two-pronged approach was employed. Firstly, a bibliometric analysis was conducted using the R bibliometrix package (<https://www.bibliometrix.org/home/index.php> (accessed on 25 September 2024)) and VOSviewer software, version 1.6.20 [44,45]. This analysis leveraged data from the Scopus database to uncover emerging trends and frequently explored topics within the field of crop disease detection.

The creation of the network maps from VOSViewer was based on keyword co-occurrences, aimed at identifying the structural connections within the research landscape. Author keywords were selected as the unit of analysis, with the full counting method applied to provide equal weight to each co-occurrence. This approach allowed a detailed examination of keyword relationships, where node proximity on the map indicated term relatedness, while clusters suggested distinct research themes or subfields.

Regarding the precision of these clusters, the methodology ensures that identified clusters offer an initial framework for interpreting core topics within the field. However, due to limitations inherent in automated clustering, such as potential overlaps between thematic areas or the absence of nuanced context, further analysis was necessary. Consequently, a more detailed examination of individual papers was conducted. This secondary analysis involved a fine-grained review of selected papers based on topics in Figure 1, allowing for

a more accurate interpretation of research themes, emerging trends, and the intellectual structure of the field.

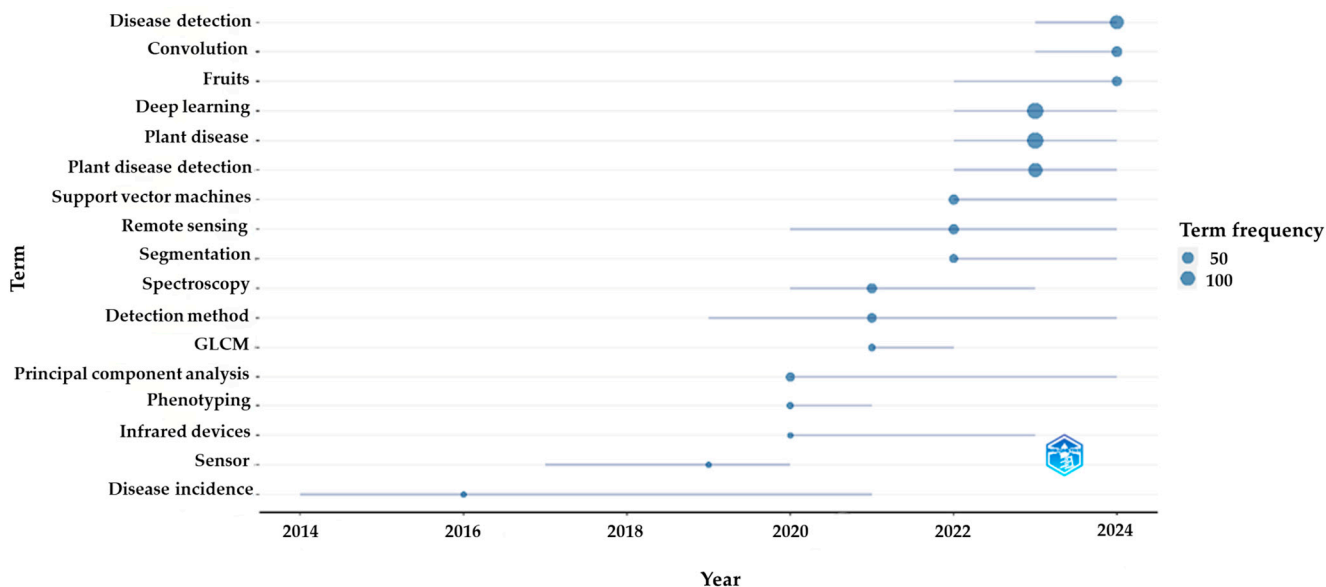


Figure 1. Temporal dynamics of research trends in crop disease detection topics.

This combined approach provides a more nuanced perspective on the research landscape, highlighting not only the trending topics but also the prevalent methodologies in plant disease detection based on artificial intelligence techniques.

Figure 1 unveils the evolving research trends in crop disease detection over the past decade (between 2012 and 2024). The term frequency on the y -axis indicates the prevalence of specific research topics within the analyzed body of literature. As the x -axis progresses through the years, a clear upward trajectory emerges, signifying a growing global focus on combating plant diseases.

Unsurprisingly, “plant disease detection” itself leads greatest throughout the ten-year period, highlighting its enduring importance. However, a closer look reveals a fascinating shift towards artificial intelligence-based (AI) techniques. The surging popularity of terms like “deep learning” and “convolutional neural networks” underscores the dominance of AI in contemporary research. The substantial rise in these terms, particularly when compared to established methods like “support vector machines”, suggests a paradigm shift towards AI-powered automated detection systems.

Intriguingly, Figure 1 also unveils a surge in interest for some exciting new research directions. The rise of “spectroscopy” signifies a growing interest in analyzing the unique spectral signatures of plants to identify diseases. Similarly, the increasing prevalence of “phenotyping” indicates the exploration of how observable plant characteristics like growth rate or size can be used to detect subtle health changes indicative of disease. Finally, the significant upward trend for “remote sensing” highlights the potential of using satellites or drones to monitor vast crop areas and detect potential disease outbreaks on the field scale.

The following analyses were then conducted in the literature from January 2012 to May 2024, considering that prior to this period, the research done were preliminary works and too scarce to be significant.

2.2. Data Retrieval and Extraction

Scopus was used to select metadata information for this study, as it is an authoritative database offering extensive coverage of the literature and is widely recognized for citations. Additionally, Scopus enables the exporting of up to 2000 publications at once, making it a commonly used reference database for several bibliometric analyses. To focus on the relevance of studies and increase consistency, a set of inclusion and exclusion criteria was

established [46]. These criteria are essential to provide clear guidelines for this review and to control its scope and size. The inclusion and exclusion criteria of this review are provided within Table 1.

Table 1. Inclusion and exclusion criteria used to define the search area of the review.

Inclusion Criteria	Exclusion Criteria
2000–2024	Before 2000
Peer-review and grey literature	Websites and project pages
English	Beyond English
Scopus	Other search engines
Keywords: plant disease detection, artificial intelligence, image, sensing	Other plant disease biology-based detection methods

The inclusion and exclusion criteria are designed to ensure that the studies included in the review are relevant to the research question and of high quality. The inclusion criteria were data of a publication between 2000–2024, the peer-reviewed and grey literature, written in English, sourced from Scopus and Google Scholar, and focused on crop disease detection based on artificial intelligence and image processing. The inclusion criteria were defined to select studies that meet the specific requirements essential for this review and relevant to the research question.

On the other hand, the exclusion criteria were established to filter out studies that do not meet these requirements. Studies published before 2000, from websites and project pages, written in languages other than English, sourced from other search engines, and employing other crop disease biology-based detection methods such as the following: detecting the spores without symptoms (PCR) [47] or based on the thermal needs of the pest reproduction cycle (meteorological) [48] were excluded. By applying these criteria, the review ensures that the included studies are both relevant and of high quality, thereby enhancing the credibility and utility of the review.

Overall, the carefully established inclusion and exclusion criteria help maintain the focus and quality of the review, ensuring that the studies considered are pertinent to the research objectives and meet high standards. This structured approach not only streamlines the review process but also increases the reliability and relevance of the findings, ultimately contributing to a more robust and impactful study.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines was used to ensure a transparent and standardized approach in conducting this review. Specifically, we followed the PRISMA checklist to structure our methodology, reporting, and presentation of results. The guidelines helped us in ensuring the rigor and reproducibility of our review process [49]. In this review the Preferred Reporting Items for Reviews and Meta-Analyses (PRISMA) method was applied (Figure 2).

The systematic exploration of crop disease detection, sensing technologies, artificial intelligence (AI), and imaging techniques began with an initial search on SCOPUS, yielding a corpus of 1409 relevant papers. A first trial based on the title and the abstract has eliminated 36 documents out of the topic. For example, we considered, out of the scope of this review, studies where the goal was to predict the presence of the disease based on meteorological conditions combined with agronomical parameters like Kundu et al. [50] or Nie et al. [51]. The cleaned total corpus was used to make the trends, but then to extract information, a second trial was performed to eliminate reviews (45) with not enough data for our research and proceedings papers (737) which were not accessible, then other studies were eliminated because their main research objective was to improve algorithms without mentioning the crop or the disease clearly (56). Eight hundred and seventy-four (874) papers were excluded, leaving a focused set of 535 papers for further analysis. This subset formed the foundation for a structured literature review, meticulously organized into five pivotal topics. The first topic, “Acquisition Methods and Data Sources”, delved into the varied methodologies and sources employed in gathering data for crop disease detection

via sensing technologies and AI. The second area, “Study Scale”, investigated the spectrum of scales adopted in research endeavors, encompassing laboratory experiments, field trials, and remote-sensing applications. “Algorithm Used” scrutinized the diverse array of AI algorithms implemented for disease detection in plants, encompassing machine learning, deep learning, and other computational techniques. Additionally, “Studied Disease” categorically explored the types of diseases scrutinized in the literature, shedding light on their characteristics and nuances. Lastly, the topic “Crop Type” delved into the specific plant species or crop types targeted within the reviewed studies. The meticulous organization into these five thematic domains facilitated a comprehensive analysis, offering insights into trends, patterns, and advancements within the realm of crop disease detection. This approach systematically delineated diverse approaches, highlighted emerging applications, identified research gaps, and paved the way for a holistic synthesis of the current state of research in this field, thereby providing a valuable framework for further investigation and scientific exploration.

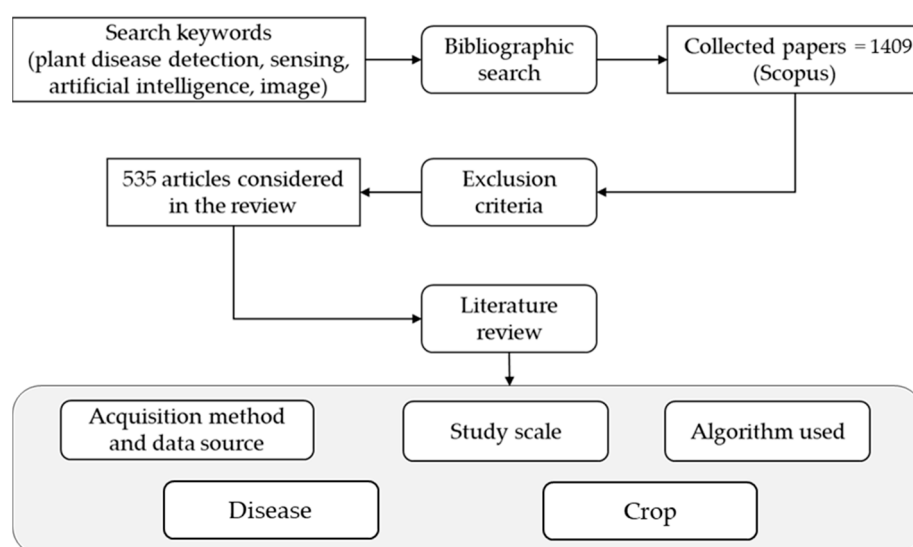


Figure 2. Flowchart of the methodology for collecting data about plant disease identification using artificial intelligence and image data.

Several working scales have been identified during the literature analysis, the scale report, the part of the crop that has been analyzed, and the environment background where data have been collected. Firstly, there are terms which only consider the data treating a single part of the crop, taking the data out of the field on a neutral or uniform background: “Fruit”, “Leaf”, “Panicle”, “Pulp”, and “Stem”. Secondly, there are data taken on a single plant called “Plant” or “Tree” with a more or less uniform background but without mixing several plants together. Thirdly, there is a mixture of parts of the plants with nearly no place to have a background: “Fruits”, “Leaves”, “Pods”, and “Spikes”. Four correspond to several plants together, with no place to have the background close to a crop field but the image is too close to catch the variability at the field level, which have been called “Plants”, and the last scale represents the data collection of the field crop called “Field” including all the plants parts, the background, and the variability within the field. There could also be a mixture of two plant parts like fruits and leaves together, which has been indicated with an “&”.

3. Results

3.1. Bibliometric Analysis

Figure 3 presents a thematic clustering visualization, that unveils the evolving landscape of crop disease detection research between 2000 and 2024. The information is gleaned from keywords extracted from titles, abstracts, and keywords of academic publications

within the SCOPUS database. The size of each node in the cluster directly corresponds to the relative frequency of its associated keyword.

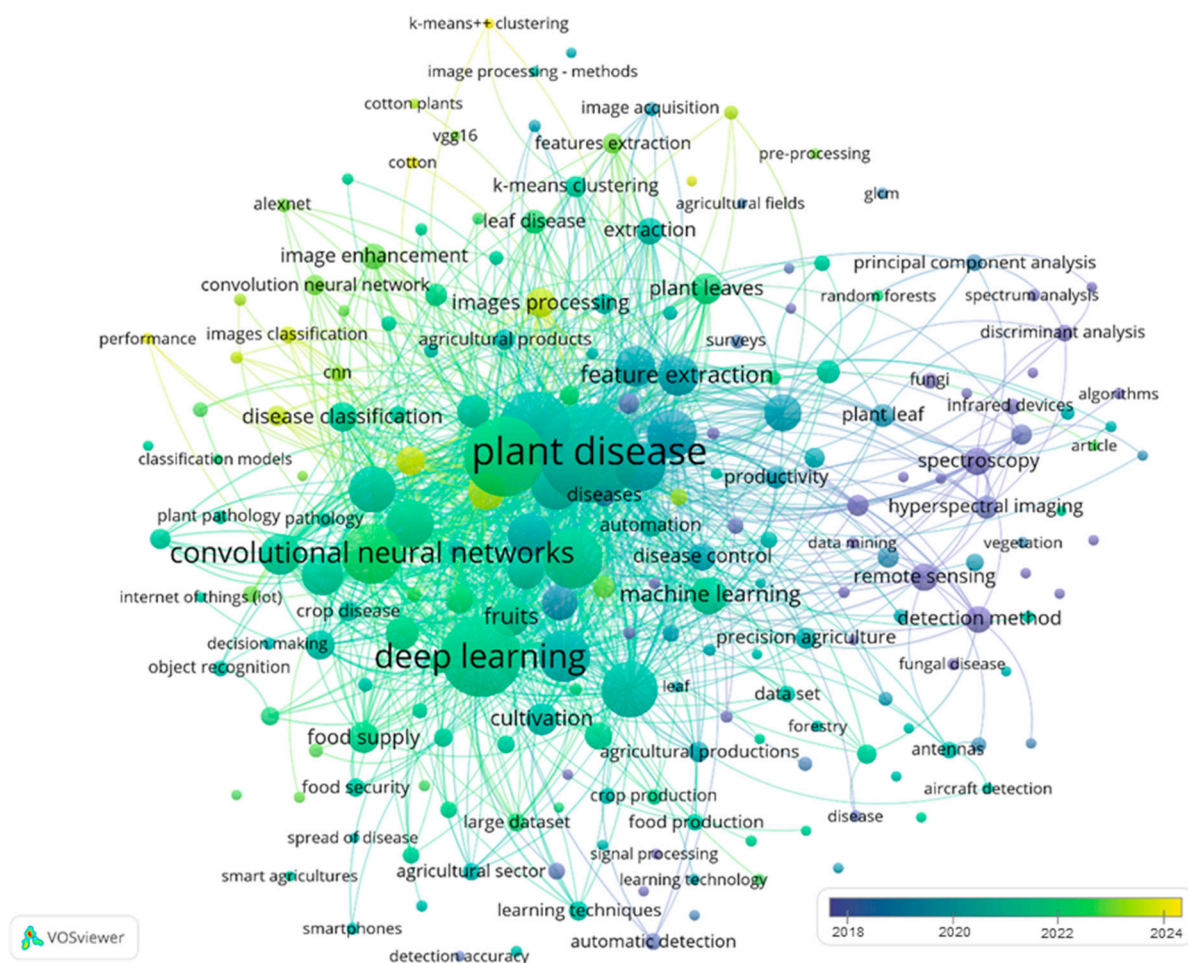


Figure 3. Thematic clustering of the topics identified from the keywords as well as their temporal evolution based on data collected from 2000 to 2024. The node size of a topic is proportionate to its relative frequency.

The clustering map predominantly shows topics from 2018 to 2024 because these years reflect a period of intensified research and significant advancements in crop disease detection through remote sensing and machine learning. Although the dataset spans from 2000 to 2024, earlier years had comparatively fewer publications or lower keyword frequencies, making them less prominent in the visualization. The clustering method highlights periods with dense, high-frequency keyword occurrences, hence the concentration on recent years where techniques like convolutional neural networks (CNNs) and deep learning became widely adopted and transformative in this field.

At the center of the clustering map, a prominent cluster emerges around key terms, including “plant disease”, “convolutional neural networks (CNNs)”, “deep learning”, and “feature extraction”. This central concentration underscores the dominance of CNNs and deep learning as dominant approaches for extracting diagnostically relevant features from imagery in the field of crop disease detection research.

Shifting to the left cluster, we encounter a thematic cluster dominated by terms like “image processing methods”, “image enhancement”, “pre-processing”, and “principal component analysis (PCA)”. These techniques likely serve as the preparatory steps before feeding images into CNNs for disease detection purposes.

On the other hand, the right cluster revolves around keywords such as “classification models”, “spectroscopy”, “plant pathology”, and “hyperspectral imaging”. This suggests that researchers are increasingly exploring spectroscopic techniques, in conjunction with classification models, as a powerful tool for detecting plant diseases.

Further exploration reveals a cluster positioned at the bottom right, centering on “IoT”, “machine learning”, “remote sensing”, and “precision agriculture”. This cluster signifies a fascinating trend: the incorporation of these emerging technologies into crop disease detection within the agricultural sector. This integration has the potential to revolutionize how we monitor and manage crop health across vast fields.

Finally, the placement of terms along the timeline provides valuable insights into their emergence and prominence over time. For instance, “k-means clustering” and “support vector machines (SVM)” appear on the left side of the map, hinting at their prevalence in earlier research. In stark contrast, terms like “deep learning” and “random forests” appear on the right, indicating a significant rise in their use in recent years. This visual representation underscores the dynamic nature of plant disease detection research, constantly adapting and embracing new advancements in the field.

To provide further and more in-depth insights into how the research in crop disease detection evolved, text mining was conducted to reveal prominent topics in the 535 sampled papers (Figure 4). The expressed topics that the papers claim to cover (i.e., keywords) fall in five main clusters: (1) the red cluster on plant disease detection methods; (2) the magenta cluster on the type of algorithms used for crop disease detection; (3) the yellow cluster of crop type where disease detection was performed; (4) the blue cluster for the dataset and learning techniques and (5) the green cluster for the study scale. These clusters, while informative, are based on co-occurrence patterns and inherently feature some overlap between keywords. For example, certain keywords may appear within a cluster even if their relevance is more closely aligned with another theme. This overlap reflects the interconnected nature of research areas and underscores the complexity of categorizing topics strictly by co-occurrence. Nonetheless, these clusters provide a structured view of the field, showing both dominant themes and how various aspects of crop disease detection research intersect and evolve. However, a more refined analysis is presented in the following sections, where results are obtained from a detailed data analysis of the selected papers.

The Sankey diagram in Figure 5 offers a compelling snapshot of the research landscape in crop disease detection using artificial intelligence and image processing. It visually depicts the interplay between the most active countries contributing to this field, the prevalent research themes, and the leading journals publishing this work. Countries like India, China, and the USA stand out on the left axis, indicating a strong research presence in this domain. The center axis showcases the core keywords, with “deep learning”, “machine learning”, and “plant disease detection” taking center stage. This reaffirms the dominance of AI techniques in contemporary research in this field. The width of the connecting lines between these keywords and countries like India suggests a significant focus on these AI-powered approaches in these regions.

The Sankey diagram provides a comprehensive visualization of the global research landscape in agricultural technology, with a particular focus on plant disease detection and the application of AI methods.

The rightmost column of the diagram lists prominent journals that serve as outlets for this research topic. The significant presence of journals such as “Computers and Electronics in Agriculture” and “IEEE Access” highlights a notable intersection between agricultural research and technological or engineering disciplines, underscoring the interdisciplinary nature of this research domain. The frequent publication in these outlets reflects the global research community’s commitment to cross-disciplinary approaches, integrating innovations in both biosciences and computational sciences to address complex challenges in agriculture. The thickness of the lines connecting these journals to keywords like “plant disease detection” and “deep learning” implies a strong emphasis on these specific image

analysis techniques within the published works. This co-occurrence analysis provides valuable insights into the current trends and focus areas within this field.

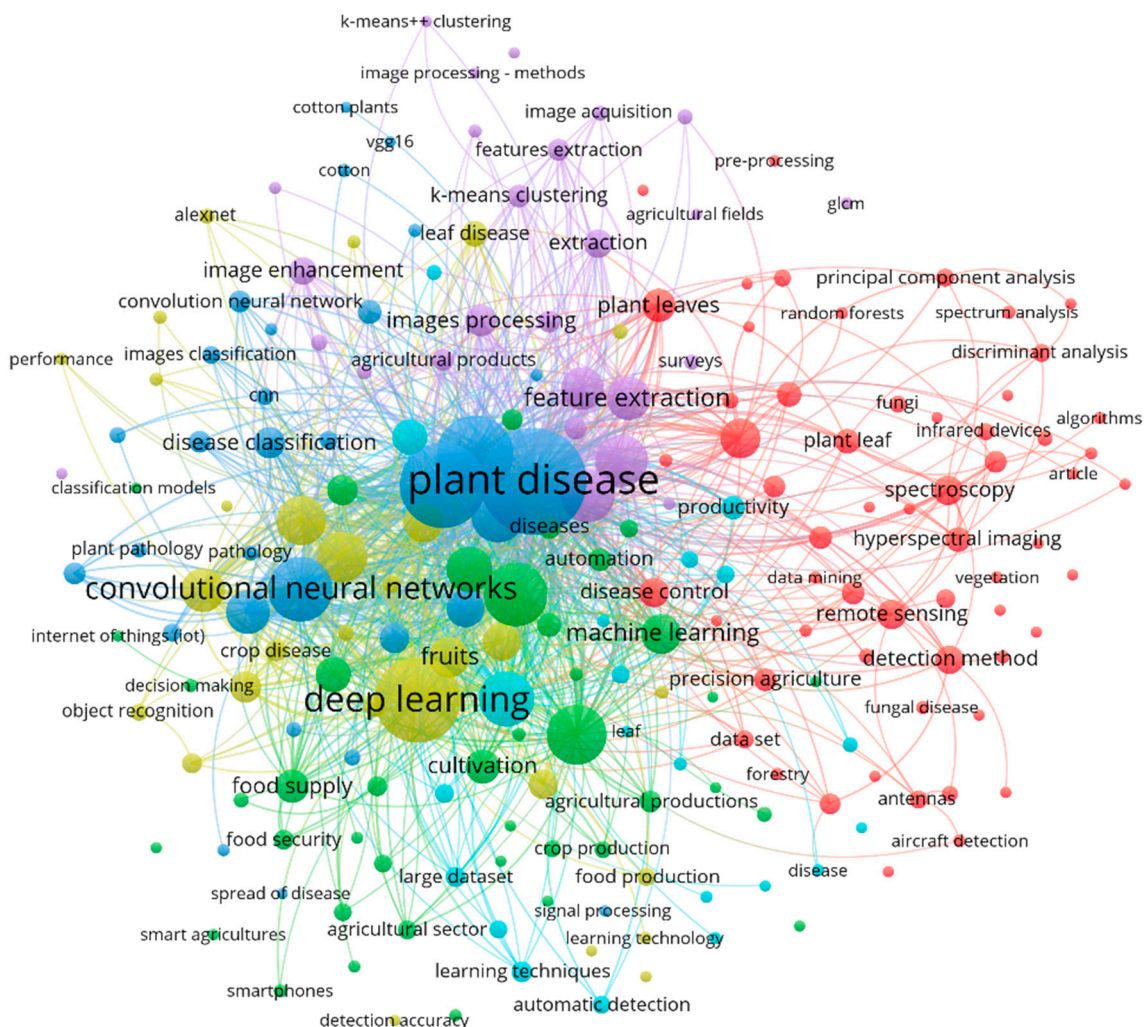


Figure 4. Thematic clustering of the topics identified from the keywords based on data collected from 2000 to 2024. The node size of a topic is proportionate to its relative frequency.

The central column delineates key research themes and methodologies prevalent in this field of research. “plant disease detection” is identified as a major theme, reflecting the pressing need for solutions to mitigate crop loss due to diseases. Methodologies applied in this research area include “deep learning”, “machine learning”, “Convolutional Neural Networks (CNNs)”, and “image processing”. These connections illustrate that advanced AI and image-processing techniques are widely used across countries. The inclusion of various AI-based approaches indicates a trend towards integrating sophisticated machine learning models to address agricultural challenges, particularly in plant health monitoring and automated disease detection.

Keywords such as “plant disease detection” and “deep learning” exhibit connections to multiple countries and journals, underscoring their central role in agricultural research aimed at enhancing food security and crop resilience. The choice of publication venues demonstrates the importance of interdisciplinary journals that bridge agriculture, engineering, and computer science, facilitating the dissemination of innovative technologies applicable to agriculture.

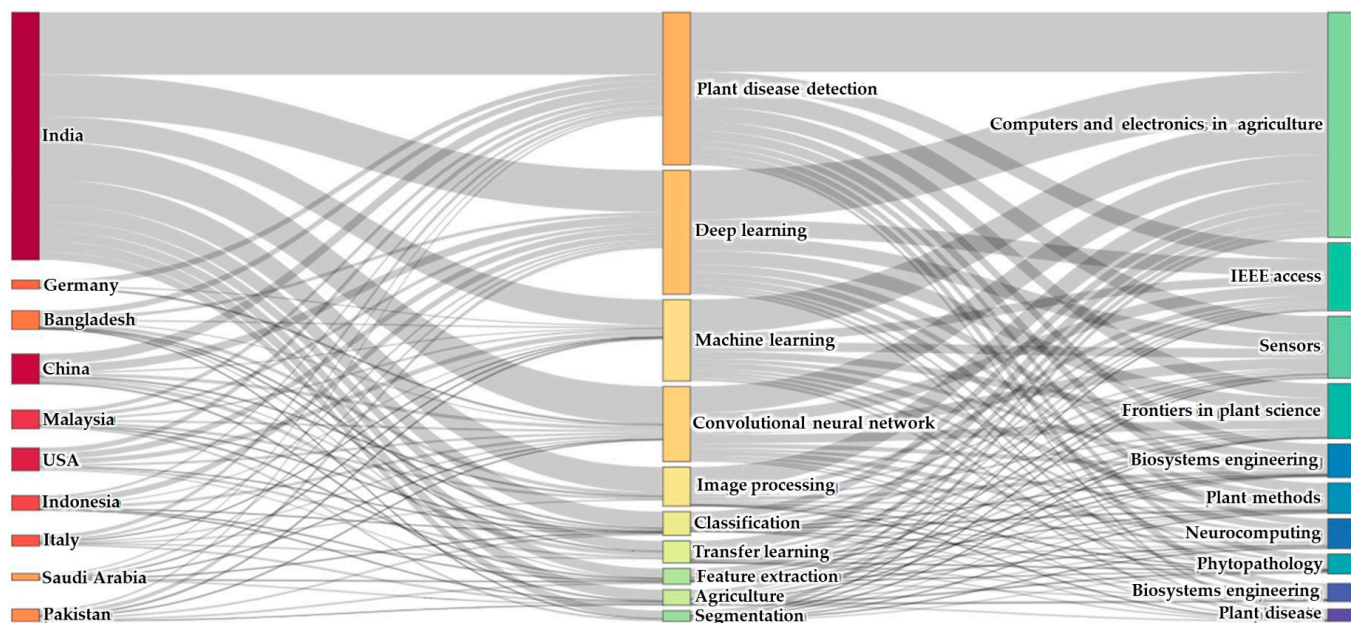


Figure 5. Sankey diagram analysis of global research trends in crop disease detection using artificial intelligence and image processing for the period between 2000 and 2024.

The leftmost column lists the countries actively contributing to this field. The diversity in country participation underscores the international scope of research in agricultural technology.

By identifying the leading research hubs, the dominant themes, and the preferred publication channels, this Sankey diagram serves as a springboard for further exploration of specific research areas within the realm of AI-powered crop disease detection. The Sankey diagram allows researchers to identify potential collaborators from active countries, delve deeper into specific AI techniques highlighted by the keywords, and target relevant journals for their own research contributions.

In the recent publications included in our analysis, there is a notable prevalence of the term “plant” rather than “crop”. This observation can be attributed to the fact that many of the authors contributing to this body of research come from non-agronomic institutions. These researchers often publish their findings in journals that are not specifically focused on agricultural sciences. As a result, the terminology they use tends to emphasize a broader biological context, favoring “plant” over the more specific agricultural term “crop”. This trend is also reflected in Figures 3 and 4, where the prominence of the word “plant” indicates a shift in focus toward a more general understanding of plant health and disease, rather than a focus solely on agricultural production.

3.2. Analysis of Disease in the Literature

The extraction of the data retrieved in this systematic review based on the research and review articles in review is summarized in Table 2, where we identified the crops concerned by the studies, the diseases detected or identified, and the study scale.

Table 2. Examples of studies performed on crop disease detection via machine learning techniques listed by crop type.

Crop	Disease	Study Scale *	Acquisition Methods **	Citations
Almond (<i>Prunus amygdalus</i>)	Leaf blotch (<i>Polystigma ochraceum</i>)	Leaves	UAV (RGB)	[52]
Avocado (<i>Persea americana</i>)	Laurel wilt (<i>Raffaelea lauricola</i>); Phytophthora root rot (<i>Phytophthora</i> spp.)	Tree	Multispectral camera	[53]

Table 2. Cont.

Crop	Disease	Study Scale *	Acquisition Methods **	Citations
Apple (<i>Malus domestica</i>)	Alternaria leaf blotch (<i>Alternaria</i> spp.), Apple black spot (<i>Venturia inaequalis</i>), and apple leaf miner (<i>Lyonetia clerkella</i>)	Leaf, Tree	Photo (Plant Village) Own photo database (VIS)	[54–58]
Asparagus (<i>Asparagus officinalis</i>)	Purple spot disease (<i>Stemphylium vesicarium</i>)	Plant	Photo (VIS & IR) and Satellite	[59]
Banana (<i>Musa</i>)	Banana fusarium wilt (<i>Fusarium oxysporum</i> f. sp. <i>cubense</i>)	Plant	UAV	[60–62]
Barley (<i>Hordeum vulgare</i>)	Powdery mildew (<i>Blumeria graminis</i> f. sp. <i>hordei</i>)	Leaf	RGB	[63]
Bean (<i>Phaseolus vulgaris</i>)	Rust (<i>Uromyces phaseoli</i> var. <i>typica</i>) and Angular leaf spot (<i>Pseudocercospora griseola</i>)	Leaf	Photo (VIS)	[64,65]
Cardamon (<i>Elettaria cardamomum</i>)	Colletotrichum Blight (<i>Colletotrichum gloeosporioides</i>) and Phyllosticta Leaf Spot (<i>Phyllosticta capitalensis</i>)	Leaves	Photo (VIS)	[66]
Cassava (<i>Manihot esculenta</i>)	Brown leaf spot (<i>Mycosphaerella henningsii</i>), Red mite damage (<i>Tetranychus urticae</i>), Green mite damage (<i>Mononychellus tanajoa</i>), Cassava brown streak virus, Cassava mosaic virus	Leaf	Photo (VIS) Photo (Kaggle)	[67,68]
Citrus	Citrus black spot (<i>Phyllosticta citricarpa</i>), Citrus bacterial canker (<i>Xanthomonas citri</i> subsp. <i>Citri</i>), Huanglongbing citrus greening (<i>Candidatus Liberibacter asiaticus</i>)	Leaves, Leaf	Photo (RGB) Hyperspectral	[69–74]
Coffee (<i>Coffea arabica</i>)	Leaf miner (<i>Leucoptera coffeae</i>) and Rust (<i>Hemileia vastatrix</i>)	Leaves	UAV	[75]
Cotton (<i>Gossypium hirsutum</i>)	Several	Leaf, Plants	Photo (VIS) Photo (Plant Village) UAV	[76–79]
Cucumber (<i>Cucumis sativus</i>)	Several	Leaf	Photo (Plant Village)	[80]
Durian (<i>Durio zibethinus</i>)	Several	Leaf	Photo (VIS)	[81]
Eggplant (<i>Solanum melongena</i>)	Fruit rot, Alternaria leaf spot (<i>Alternaria</i> sp.), Little leaf of Brinjal (phytoplasma), Mosaic virus, Collar rot (<i>Sclerotinia sclerotiorum</i>)	Leaves, Fruit, Plant	Photo (VIS)	[82]
Grapevine (<i>Vitis vinifera</i>)	Grapevine flavescence dorée phytoplasma, Yellows, Esca (<i>Phaeoconiella chlamydospora</i> , <i>Phellinus punctatus</i> , <i>Fomitiporia mediterranea</i> , <i>Phaeoacremonium minimum</i>), Downy mildew (<i>Plasmopara viticola</i>)	Leaves Leaf	RGB; Spectroradiometer Photo (in vitro) Photo (Plant Village)	[36,83–87]
Guava (<i>Psidium guajava</i> L.)	Guava rust (<i>Austropuccinia psidii</i>), Scabby fruit canker (<i>Pestalotia psidii</i>), Mummy disease (<i>Gloeosporium Psidii</i>)	Fruits & Leaves	Photo (VIS)	[61,88]

Table 2. Cont.

Crop	Disease	Study Scale *	Acquisition Methods **	Citations
Maize (<i>Zea mais</i> L.)	Northern corn leaf blight (<i>Exserohilum turcicum</i>), Southern corn leaf blight (<i>Bipolaris maydis</i>), Common rust (<i>Puccinia sorghi</i>)	Leaf	Photo (VIS)	[89–95]
Mango (<i>Mangifera indica</i> L.)	Sooty mould (<i>Capnodium salicinum</i>)	Leaf, Leaves	Photo (Plant Village, leaf snap)	[96–98]
Melon (<i>Cucumis melo</i> L.)	Powdery mildew (<i>Sphaerotheca fuliginea</i>)	Leaves	Photo (VIS) UAV	[37,99]
Mulberry (<i>Morus nigra</i>)	Leaf rust (<i>Peridiospora mori</i>) and Leaf spot (<i>Mycosphaerella mori</i>)	Leaf	Photo (VIS)	[100]
Oil palm (<i>Elaeis guineensis</i>)	Basal stem rot of oil palm (<i>Ganoderma boninense</i>)	Leaf	Photo (VIS) FTIR and Raman spectroscopy	[8,101]
Olive tree (<i>Olea europaea</i>)	Several	Leaf	Photo (VIS)	[102,103]
Onion (<i>Allium cepa</i> L.)	Onion Smudge (<i>Colletotrichum circinans</i>)		Satellite (VIS-NIR)	[104,105]
Papaya (<i>Carica papaya</i> L.)	Begomovirus (<i>Geminiviridae</i>)	Leaf	NIR and FT-IR ATR	[106]
Pea (<i>Pisum sativum</i> L.)	Rust disease (<i>Uromyces viciae-fabae</i> Pers. de-Bary)	Leaf	Microscopic images	[107]
Peanuts (<i>Arachis hypogaea</i>)	Peanut stem rot (<i>Athelia rolfsii</i>)	Leaves	UV, VIS, NIR, Thermal	[108]
Pepper (<i>Capsicum</i> spp.)	Pepper yellow leaf curl virus (PepYLCIV), Several	Leaf, Pulp, Stem	FT-IR Photo (VIS, Plant Village + pepper diseased dataset)	[109–113]
Pigeon pea (<i>Cajanus cajan</i>)	Fusarium wilt (<i>Fusarium udum</i>), Pigeonpea sterility mosaic virus (PPSMV), Ashy stem blight (<i>Macrophomina phaseolina</i>), Phytophthora blight (<i>Phytophthora drechsleri</i> f. sp. <i>cajani</i>)	Leaf	Photo (VIS)	[114]
Plum (<i>Prunus</i> subg. <i>Prunus</i>)	Several	Leaves, Leaves & Fruit	Photo (VIS)	[115]
Potato (<i>Solanum tuberosum</i>)	Early blight (<i>Alternaria solani</i>), Late blight of potato (<i>Phytophthora infestans</i>)	Leaf	Photo (Plant Village)	[116–119]
Rapeseed (<i>Brassica napus</i> L.)	Sclerotinia stem rot (<i>Sclerotinia sclerotiorum</i>)	Leaves	Hyperspectral	[120]
Rice (<i>Oryza sativa</i>)	Bacterial leaf blight (<i>Xanthomonas oryzae</i> pv. <i>oryzae</i>), Brown spot of rice (<i>Cochliobolus miyabeanus</i>), Tungrovirus <i>oryzae</i> , <i>Entyloma oryzae</i> (leaf smut of rice)	Leaves, Panicle	Photo (VIS)	[121–130]
Rose (<i>Rosa</i> sp.)	Powdery mildew of rose (<i>Podosphaera pannosa</i>) and Gray mold of roses (<i>Botrytis cinerea</i>)	Leaf	Thermal and visible images	[131]

Table 2. Cont.

Crop	Disease	Study Scale *	Acquisition Methods **	Citations
Solanum	Blight (n.d.), several	Leaf	Photo (Plant Village)	[132–134]
Soybean (<i>Glycine max.</i>)	Nematodes cyst nematode, Anthracnose of soybean (<i>Colletotrichum truncatum</i>) Wildfire (<i>Pseudomonas syringae</i> pv. <i>tabaci</i>)	Field, Pods, Leaves,	Satellite (hyperspectral) VIS+NIR	[135–137]
Squash (<i>Cucurbita</i>)	Cucurbit powdery mildew (<i>Podosphaera xanthii</i>)	Plant	UAV (multispectral)	[138]
Strawberry (<i>Fragaria x ananassa</i>)	Anthracnose (<i>Colletotrichum fragariae</i>), Gray mold of strawberries (<i>Botrytis cinerea</i>)	Leaf	Photo (VIS) Hyperspectral	[139–141]
Sugar beet (<i>Beta vulgaris</i>)	Cercospora leaf spot (<i>Cercospora beticola</i>)	Plants	UAV	[19,142,143]
Sugarcane (<i>Saccharum officinarum</i>)	Orange rust disease of sugarcane (<i>Puccinia kuehnii</i>), Sugarcane yellow leaf virus (ScYLV), Eye spot disease of sugarcane (<i>Helminthosporium saccharari</i>), Brown leaf spot of sugarcane (<i>Cercospora longipies</i>), Red rot of sugarcane (<i>Colletotrichum falcatum</i>)	Leaf	Photo (VIS)	[144,145]
Tomato (<i>Solanum lycopersicum</i>)	10 diseases, early blight (<i>Alternaria solani</i>), Tomato Spotted Wilt Virus (TSWV)	Leaf	Photo (Plant Village) Own database VIS + NIR Hyperspectral	[24,146–155]
Green Tea (<i>Camellia sinensis</i>)	Blister blight of tea (<i>Exobasidium vexans</i>), Leafhopper, Caterpillars, Mosquito, Yellow mite	Leaf	Photo (VIS)	[156]
Walnut (<i>Juglans regia</i> L.)	Diseased (n.d.)	Leaf	Photo (VIS)	[157]
Wheat (<i>Triticum aestivum</i> L.)	Wheat stripe (yellow) rust (<i>Puccinia striiformis</i> f. sp. <i>tritici</i>), Wheatbrown rust (<i>Puccinia triticina</i>) Fusarium head blight (<i>Fusarium graminearum</i>)	Field, Spikes, Leaves	UAV VIS Hyperspectral + Fluorescence Photo (VIS)	[20,158–167]

* Fruit, leaf, panicle, pulp, stem: a single organ photo in a neutral environment; fruits, leaves, spikes: several same parts of a plant pictured together; plant, tree: a single entire plant of a crop in an image with a neutral background; plants: several entire plants together; field: photo take above the crop, leaves, stems and soil included in the photo.** RGB: Red Green Blue; VIS: visible; NIR spectroscopy; Near Infrared; FT-IR: Fourier-Transform Infrared spectroscopy; ATR: Attenuated Total Reflection; UAV: Unmanned Aerial Vehicle; n.d.: not defined.

3.2.1. Study Scale

Based on the objectives and aims of each study, study scales are different. Most manuscripts retrieved have, as the main study scale, a single leaf (Table 2) which has been taken out of the plant to be placed in a neutral background that will be eliminated easily at the first image treatment avoiding any interference with data acquisition. In addition, most of the documents retrieved used an online database to find leaves that were already annotated (diseased and healthy), Plant Village (<https://datasets.activeloop.ai/docs/ml/datasets/plantvillage-dataset/> accessed on 9 September 2024) being the most common. This joins the precedent point, alerting us about how the disease detection subject is mainly treated from an algorithmics or computational vision, with few agronomical points of view, since annotated photos without an environmental context is easier to treat. There are a few

studies where photos were taken on an entire plant where several leaves, and stem, or fruits were included. Lastly, some research were based on UAV [52,60,75] or satellite [59,105] data acquisition, considering several plants at the same time with a complex environment that includes light/shadowing of some plants, ground presence, different maturity stages of plants, several layers of leaves with a differentiate disease progression, or the presence of weeds. These complex environments are difficult to treat, and the pre-treatment of the image is longer and difficult.

3.2.2. Crop and Disease

The most studied crops were tomato [146], rice [130], wheat [20] and maize [90] (Table 2), where other crops have been neglected or present little research. Another trend is that quite a lot of documents (not reported in Table 2) do not focus the research on a particular crop but were looking for the identification of one or several diseases [168–170], and that they do not care about the crop nor the disease and there is only research on distinguishing health and diseased leaves [21]. The common characteristic of those manuscripts is that the work focused on public photos available in databases like the Plant Village. In nearly all the cases, the analysis and the identification are made between the diseased leaf and a healthy leaf. At the level of UAV [20,171] and satellite acquisition, studies were able not only to identify the disease but also started to indicate the disease pressure in the field and others started to analyze the disease severity [158,172]. Most of the studies focused on leaves with fungal diseases, but a few also studied stems [109] or fruits [82,88] diseases and others have observed the impact of insects [156] or viruses [82] on the leaves. Major crops have been studied and regarding the literature, no disease in any crop has had a particular difficulty in being identified in a particular organ when detected outside the field with a proximal data acquisition using high quality images. When it comes to the detection of the diseases in the field, the number of crops evaluated is much reduced and the results are not advanced enough when acquired with either UAVs or with satellites. First studied in a large scale, they can detect the disease when it is largely expanded and can evaluate a disease severity level but they are not accurate enough to develop a decision support system based on those acquisitions.

3.2.3. Acquisition Method and Data Source

The efficiency of artificial intelligence methodologies in plant disease detection axes on the variety of data sources is employed. A selection of these sources is guided by the research objectives and the spatial scale of the targeted disease. For instance, high-resolution ground-based imagery facilitates the detection of early disease stages in specific plant types [162]. The detailed information captured allows for an accurate examination of variations in a plant's spectral reflectance, potentially revealing disease signatures before visible symptoms manifest [155,165].

Conversely, monitoring vast fields necessitates a broader approach. In such cases, multispectral data acquired by UAVs proves advantageous [19]. These aerial platforms can be equipped with sensors that gather information beyond the visible spectrum, providing valuable insights into plant health that are imperceptible to the human eye. For example, near-infrared sensors can detect subtle changes in plant vigor, while thermal sensors can identify areas with abnormal temperature fluctuations, which are potentially indicative of disease presence [38,162,164].

The incorporation of data from supplementary sources can significantly enhance model performance. Data from weather stations and strategically placed soil sensors can contribute critical details regarding environmental factors like temperature, humidity, and nutrient levels, all of which significantly influence disease development and spread [85]. By strategically combining data from these diverse sources, plant disease detection can achieve a comprehensive and refined understanding of crop health, enabling earlier interventions and improved disease management strategies.

3.2.4. Algorithm Used and Annotation Tools

Further data processing steps are usually needed to make data ready for training. In a deep learning architecture, annotations or image labelling is a major step to supervise the algorithm and provide some regions of interest. These regions of interest generally are the objects and patterns to be detected in images. Table 3 provides a summary of the most used tools for labelling images.

Table 3. Frequently used image annotation tools.

Tool	Source	Advantages/Constraints
LabelImg	https://github.com/heartexlabs/labelimg (accessed on 10 September 2024)	Python based, open-source, needs programming skills
VGG Image Annotator (VIA)	https://www.robots.ox.ac.uk/~vgg/software/via/ (accessed on 10 September 2024)	Web-based tool, open-source, requires internet connection, some issues with large dataset
Labelbox	https://labelbox.com/customers/genetech-customer-story/ (accessed on 10 September 2024)	Python based, commercial, complex feature set
SLOTH	https://github.com/cvhciKIT/sloth (accessed on 10 September 2024)	Python based, open-source, not supported on all platforms, some issues with large dataset
Hasty	https://hasty.ai/v2 (accessed on 10 September 2024)	Cloud Annotations GUI, Commercial, auto label function
IBM Cloud Annotations Tool	https://developer.ibm.com/blogs/ibm-cloud-annotations-tool-eases-the-process-of-ai-data-labeling/ (accessed on 10 September 2024)	Cloud Annotations GUI, auto label function
RectLabel	https://github.com/ryouchinsa/Rectlabel-support (accessed on 10 September 2024)	Support only Linux environment, commercial
Labelme	https://developer.ibm.com/blogs/ibm-cloud-annotations-tool-eases-the-process-of-ai-data-labeling/ (accessed on 10 September 2024)	Python, based, open-source, some issues with large dataset
Scale	https://scale.com/image (accessed on 10 September 2024)	Cloud Annotations GUI, auto label function, commercial
SUPERVISELY	https://supervise.ly/ (accessed on 10 September 2024)	Cloud Annotations GUI, auto label function, commercial

These advantages and constraints can vary based on the specific requirements of the project and the preferences of the annotators. Some of these constraints may not be significant for certain research, while others may be deal breakers. Table 3 summarizes frequently used tools for image annotation.

Annotation tools exhibit significant heterogeneity in design and functionality to address diverse research requirements. User interfaces can be graphical (GUI), web-based, or command-line driven. Platform compatibility varies, with some operating tools being system-specific or requiring additional software libraries. Additionally, annotation formats differ, with support ranging from the widely used PASCAL VOC XML to COCO JSON [173]. Feature sets further distinguish these tools, with some offering collaborative annotation, automation capabilities, and integrated data management, while others prioritize the core annotation process. Finally, cost models diverge, with open-source options like LabelImg freely available and commercially developed tools like RectLabel requiring licensing fees.

Only a few of the references retrieved have used one of these annotation tools, for example [170], where most studies prefer to use already annotated images like those found in the Plant Village database. Labelling is a tedious step which seems to have not been largely combined with research developing the algorithms for disease detection.

When choosing an annotation tool, it is important to consider the specific requirements of the project, such as the format of the data, the type of annotation, and the preferences of the annotators.

Table 4 shows the use frequency of various algorithms used for plant disease prediction. Convolutional Neural Networks (CNNs) are the most frequent algorithm, cited in 37% of the references, followed by Generative Adversarial Networks (GANs) at 18%.

Table 4. Frequently used algorithms in plant disease detection within the references in the constituted database.

Algorithms	Use Frequency (%)	Example References
CNN	37	[174–177]
DCNN	3	[88]
R-CNN	4	[178]
Mask R-CNN	1	[158]
Faster R-CNN	2	[70]
YOLO	3	[70,146,179]
RFCN	3	[180]
GAN	18	[24,181,182]
VGG	13	[183]
SVM	16	[184]

This suggests that CNNs and GANs are popular choices for researchers in this field. CNNs are a type of deep learning algorithm that have been very successful in image recognition tasks. They are well suited for analyzing images of plant leaves to detect diseases. GANs are a type of generative model that can be used to create synthetic data. This can be useful for training CNNs when there is a limited amount of real-world data available.

Other algorithms listed in the table include Support Vector Machines (SVMs) and VGG models, both at 16% and 13%, respectively. These are all machine learning algorithms that can be used for classification tasks. In the context of plant disease prediction, they can be used to classify images of plant leaves as healthy or diseased.

Results also show the use of various deep learning object detection models, including R-CNN, Mask R-CNN, Faster R-CNN, and YOLO. These models are designed to detect and localize objects in images. In the context of plant disease prediction, they could be used to identify the specific regions of a plant leaf that are infected with disease.

At the field level, high-resolution images captured by handheld devices are analyzed using models like CNNs, known for their robust feature extraction in detecting specific leaf diseases, such as tomato blight or grape mildew [185,186]. Transfer learning, which adapts pre-trained CNNs to specific agricultural datasets, enhances detection efficiency. Additionally, Support Vector Machines (SVMs) and Random Forests (RF) offer reliable classification based on handcrafted features (e.g., color, texture), ideal for smaller datasets and simpler disease identification tasks. These models make field-level disease detection accessible even with limited computational resources.

Object detection models, such as YOLO and Faster R-CNN, localize disease patches for targeted pesticide application, while vegetation indices (e.g., NDVI, EVI) reveal early stress markers. Satellite-based detection, often using Deep Convolutional Networks (DCNs) and temporal Recurrent Neural Networks (RNNs), monitors regional disease trends with spectral and temporal data. GANs enhance low-resolution satellite data to improve detection precision and anomaly detection with vegetation indices that helps track large-scale

disease outbreaks. Together, these ML and DL applications facilitate rapid, scalable, and data-driven disease management in agriculture.

Despite its advantages for large-scale monitoring, the use of satellite data in crop disease detection remains limited, particularly for detecting early-stage symptoms at the leaf scale. Satellite imagery, even at high resolution, struggles to capture fine-grained details, making it difficult to identify specific symptoms that are evident in close-up images, such as small lesions or discolorations on individual leaves. These leaf-level symptoms, crucial for early detection and intervention, are often imperceptible from space due to resolution constraints and atmospheric interference.

3.3. Uses of the Data Acquired

To date, few uses have been developed to use these ML or DL techniques except some mobile applications to help farmers in the identification of diseases at leaf level [187–189] whose advantages and limitations have already been reviewed [43]. A few other studies have started research on the possibility of combining ML with weather data and agronomic knowledge to find a tool that helps farmers with disease detection [190], and a few others have combined AI to detect diseases at the field level to decide when is more convenient to make the treatment [191]. However, to the date, there is a gap between the disease detection and the treatment by farmers, as most of the researchers found work at the leaf level. Research has achieved the recognition and identification of pathogens and disease symptoms compared to sane or not contaminated organs. However, they have not tested their accuracy at the field level, so we can expect that their use is limited. They could help low-skilled farmers to identify the disease, but it will require agronomical knowledge to determine if it is necessary to make a treatment, the product that needs to be applied, and the amount to be applied.

4. Perspectives and Challenges

Once the technology is developed, it will be extended to farmers' fields. Then, other issues may rise. Technically, one major problem will be the quality of the acquired images, particularly with latent symptoms and small-sized lesions. There is a challenge in capturing the diseases present in the lower leaves of the canopy, in motion but also because of the presence of shadows or bad light depending on the time of acquisition and the weather conditions. The second challenge will be the speed of data treatment before disease management actions are taken on the field.

From an agronomic point of view, another major challenge will be the annotation of diseases on leaves in non-controlled environments such as field conditions. In those situations, the progression of the diseases relies on many factors such as the meteorological conditions and the crop density. The developmental stage of each individual plant in the crop's field may not result in a uniform distribution of the disease in the field. Additionally, in general, there are several concomitant pests in a field combined with the progression of the senescence of older leaves due to natural optimization of allocation of nutrients to maximize photosynthesis in the upper leaves. Even for trained personnel, it is difficult to distinguish those symptoms combined in the canopy if the data (for annotations or for the data acquisition) are not collected with a high quality (proximal way), in which case the information will be less accurate, demanding a leaf-by-leaf annotation within a field which would be tedious and long.

On the contrary, machine learning tools do not require such detailed annotations because they are going to have a global grade of disease level (considering the global health status of the plant) with not many details, making the step of annotation quicker but less precise.

If the variable rate of application is considered, then there are several possibilities with different consequences which could be observed on field yield or produce quality, disease resistance development and disease spreading, conducting to a need for re-treatment. Once there is an identified risk on the parcel that may require a chemical treatment, it is necessary

to determine the rules that decide if a person should apply or not apply the chemical product and which quantity will be necessary. Firstly, the choice may be to cover the whole parcel but with modulated application quantities depending on the risk of infection. Secondly, the choice may be to apply the product only where the disease is present or to apply only where the disease is present with or without a surrounding margin around the target to avoid proximal contamination. Lastly, the choice may be to use a reduction of the recommended doses in cases of low risk to prevent the development of resistance by pathogens due to mutations [192].

Field-level and drone-based imaging provide high-resolution, actionable insights, enabling early detection and targeted interventions. Despite current limitations in resolution and computational demand, drones fitted with multispectral sensors should be considered for monitoring extensive agricultural areas, while there is a need to further investigate the potential of satellite data for regional crop health monitoring.

The integration of advanced sensing techniques like fluorescence imaging, spectroscopy, and thermal imaging at the leaf level represents a promising direction for crop disease detection. When combined with ML and DL models, these methods could provide precise, early-stage disease identification, allowing for timely interventions. Future research should focus on optimizing these tools for field use, potentially transforming precision agriculture with enhanced disease monitoring and management capabilities at the plant level.

The field of crop disease detection can be significantly enhanced by the adoption of new ML and DL technologies. Federated learning allows for the training of models on decentralized data sources while preserving data privacy, enabling diverse agricultural datasets from multiple farms to improve disease detection accuracy. Additionally, transfer learning and domain adaptation can optimize model performance across different crops and environmental conditions, addressing the challenge of limited labelled datasets. Ensemble learning techniques can further enhance predictive performance by combining outputs from multiple models to reduce variance and bias. Advances in edge computing will facilitate real-time data processing from IoT sensors and drones, ensuring timely disease detection and response. Furthermore, multi-modal data integration merging visual images, spectral data, soil health information, and climatic conditions promises a comprehensive understanding of crop health dynamics. Finally, enhancing user-friendly mobile applications that leverage ML and DL algorithms can empower farmers to diagnose diseases using smartphones, offering immediate guidance for effective management practices. Collectively, these innovations hold great potential in improving crop health management, increasing yields, and promoting sustainable agricultural practices.

5. Conclusions

This review shows that there are many crops where artificial intelligence using deep learning or machine learning methods have been used to detect and identify diseases. Unfortunately, even if the algorithms developed presented a high accuracy, as they are mainly developed with the image of one leaf out of an agronomical context (other leaves, other plants, or varying environmental conditions), their use remains difficult in establishing a field diagnosis.

Nevertheless, some smartphone applications may help farmers to identify the disease present in their field as a decision support system. Future research is needed to extend their use to field applications and combine them with localized treatments.

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