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Systematic Review

Trends in Machine and Deep Learning Techniques for Plant Disease Identification: A Systematic Review

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Abstract: This review explores the use of machine learning (ML) techniques for detecting pests and diseases in crops, which is a significant challenge in agriculture, leading to substantial yield losses worldwide. This study focuses on the integration of ML models, particularly Convolutional Neural Networks (CNNs), which have shown promise in accurately identifying and classifying plant diseases from images. By analyzing studies published from 2019 to 2024, this work summarizes the common methodologies involving stages of data acquisition, preprocessing, segmentation, feature extraction, and prediction to develop robust ML models. The findings indicate that the incorporation of advanced image processing and ML algorithms significantly enhances disease detection capabilities, leading to the early and precise diagnosis of crop ailments. This can not only improve crop yield and quality but also reduce the dependency on chemical pesticides, contributing to more sustainable agricultural practices. Future research should focus on enhancing the robustness of these models to varying environmental conditions and expanding the datasets to include a wider variety of crops and diseases. CNN-based models, particularly specialized architectures like ResNet, are the most widely used in the studies reviewed, making up 42.36% of all models, with ResNet alone contributing 7.65%. This highlights ResNet's appeal for tasks that demand deep architectures and sophisticated feature extraction. Additionally, SVM models account for 9.41% of the models examined. The prominence of both ResNet and MobileNet reflects a trend toward architectures with residual connections for deeper networks, alongside efficiency-focused designs like MobileNet, which are well-suited for mobile and edge applications.

Keywords: plant disease; plague; image processing; data augmentation; machine learning; deep learning

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1. Introduction

The agricultural industry is consistently under pressure to meet the demands of a growing population. However, despite recent technological advancements that have led to increased crop productivity, the approach has degraded the environment, and significant losses due to pests, pathogens, and weeds have been recorded [1]. As much as 40% of global agricultural production is lost each year due to pests that affect various crops, according to the Food and Agriculture Organization of the United Nations (FAO) [2]. One of the significant challenges facing the agricultural sector is the early detection of plant pests and diseases. Pests and diseases can cause crop destruction, as many countries depend heavily on agricultural productivity [3]. The correct identification and classification of plant pests and diseases is one of the most challenging tasks in the agricultural industry. Insect damage significantly affects agricultural yield, and the classification of insects is challenging due to their complex structure and complex species connections [4,5].

Historically, the detection of diseases in plants has been based on farmers' experiences or guidelines. Each plant disease progresses through multiple developmental phases, and in the event a disease or pest affects a crop, farmers must remain informed of the situation [6]. Therefore, the identification and detection of diseases and pests in crops or plants have become imperative given their natural susceptibility to various fungal or bacterial diseases in the field. Failing to predict the problem early can result in significant disasters, impacting both the quantity and quality of production. Moreover, disease identification techniques are time consuming and necessitate the careful selection of insecticides [7]. Despite the widespread use of pesticides, several diseases and pests continue to cause yield losses [8], and the use of pesticides often leads to a reduction in the quality of the product.

Therefore, ongoing efforts are being made to find solutions to improve and address agricultural issues, and machine learning is emerging as a promising option for identifying pests and diseases in crops. However, there are various challenges in image processing, which is a critical step for the effective functioning of such intelligent models. Issues such as the presence of shadows, noise, or changes in lighting conditions in captured crop images can lead to misclassification in disease prediction [9] and other problems. Conventional methods may not be practical due to the diverse diseases that occur in the same locations, and the same disease might have different manifestations due to the various types and local conditions. Consequently, image-based disease detection has become a significant area of research in the fields of informatics and agriculture. In recent years, the research community has shown substantial interest in the identification and categorization of plant diseases using digital images [10]. The development of computer-aided diagnostic systems for agricultural applications utilizing RGB images is not only a field of study but also a crucial and rapidly expanding one. The impact of feature sets on the classification of plants using machine learning methods and rules has been extensively studied for agricultural purposes. The accuracy assessment of machine-learning-based classification techniques demonstrates an effective performance in identifying plant diseases.

In recent years, there have been significant advancements in the field of plant disease detection through the application of machine learning (ML) and deep learning (DL) techniques. Studies by [11,12] have emphasized the existing research gaps and challenges within DL techniques. Specifically, the work of [13] focuses on Convolutional Neural Networks (CNNs) to detect leaf diseases, addressing issues such as data representation and overfitting. Moreover, ref. [14] explores DL strategies and CNN models, while ref. [15] investigates segmentation and ML classifiers achieving high accuracy despite complex backgrounds. In addition, ref. [16] reviews AI techniques for pest identification, underscoring the importance of accuracy in evaluating performance.

Therefore, this systematic review aims to answer the following research question: what are the recent advances and outcomes in the use of machine learning techniques for detecting diseases and pests in plants or leaves over the last two years? To address this, current research on the application of machine learning in plant pest and disease detection through image analysis was explored and summarized. By examining studies published from 2019 to 2024, this review seeks to provide a comprehensive and updated overview of methodologies, advancements, and best practices in the field, offering valuable insights into how machine learning can tackle the challenges of pest and disease detection in agriculture.

The main contributions of this review work include the following:

- Identifying the trend of the main image processing techniques used for the classification of diseases and pest-related plants.
- Exploring different image preprocessing strategies, such as data augmentation, to build datasets.
- Presenting the main features considered in the image segmentation to model classification models for diseases and pest-related plants.

The rest of this document is structured as follows. Section 2 outlines the methodology used for the systematic analysis, Section 3 presents the obtained results, Section 4 discusses the results, and Section 5 provides the conclusions.

This review's unique contribution lies in its integration of preprocessing, augmentation, and hybrid modeling approaches into a cohesive framework. A trend toward lightweight architectures, such as MobileNet, for resource-constrained environments and hybrid models, such as CNN-SVM, for datasets with limited variability was observed, reflecting current advances and suggesting practical applications in real-world agricultural settings.

2. Materials and Methods

This section describes our systematic approach to evaluating the effectiveness of machine learning techniques in detecting crop pests and diseases. We explain our methodology, including the selection criteria for relevant research articles, the search strategy and databases used, and the analytical methods employed to synthesize data from selected studies. This guide offers transparency and the reproducibility of our research process for other researchers to replicate.

2.1. Research Question

What are the recent advances and outcomes in the last two years regarding the use of machine learning techniques to detect diseases and pests in plants or leaves?

2.2. Methodology

The period from 2019 to 2024 was selected for this study to capture the latest advances in the field of plant disease detection and pest management using deep learning and image processing techniques. This time frame covers the latest technological innovations and methodologies that have been developed, allowing us to incorporate cutting-edge approaches and ensure that our research is in line with the current state of the art.

To complete this systematic review, we conducted a search for relevant articles following the exclusion and inclusion criteria listed below.

Inclusion criteria:

- Articles that employ machine learning techniques for pest detection in plants or leaves.
- Articles that employ machine learning techniques for the detection of disease in plants or leaves.
- Articles written in English.
- Articles published from 2019 to 2024.

Exclusion criteria:

- Articles not available in English as this language is required to ensure understanding of the content and proper analysis.
- Articles published before 2019 to focus on recent advancements and relevance.
- Articles that use non-image data as this review specifically targets image-based methods in plant disease and pest detection.
- Articles that use irrelevant data types that fall outside the scope of close-up, image-based detection such as satellite images.
- Documents other than peer-reviewed journal articles, including theses, conference proceedings, and reports to maintain a consistent level of academic rigor.
- Articles behind a high-cost paywall to ensure that all selected studies were readily accessible for comprehensive review.

We applied these inclusion and exclusion criteria to ensure the quality and relevance of the studies in the Scopus database, which was selected as the sole source for articles in this review due to its comprehensive coverage and high indexing standards, particularly in the fields of science and technology. Coupled with this, its robust indexing ensures that only reputable and rigorously reviewed studies are included, which helps maintain the reliability and accuracy of our findings [17].

The following search formula was created:

TITLE-ABS-KEY ("machine learning" AND ("plants" OR "leaves") AND "images" AND "disease" AND "detection") AND PUBYEAR > 2019 AND PUBYEAR < 2024 AND NOT ("classify") AND (LIMIT-TO (DOCTYPE, "ar"))

Initial Search

In August 2024, we conducted the literature search using the Scopus database and found a total of 447 articles. After removing duplicate entries, we were left with 438 articles. We then screened each article based on their titles and abstracts, resulting in 121 articles not meeting the required standards. This left us with 317 articles for further analysis. We proceeded with a full-text review to ensure that they met the predefined inclusion and exclusion criteria. Two independent reviewers evaluated each article to minimize bias, leading to the exclusion of 69 articles that focused on crops analyzed using sensors not intended for image analysis in this review. Furthermore, 24 articles were not available on Scopus or were only accessible through paid services with prohibitively high costs, limiting their accessibility. Furthermore, 46 articles were excluded because they analyzed irrelevant image types, such as satellite images. As a result, the systematic review included a total of 178 articles. Data extraction focused on collecting key information, such as the machine learning models used, performance metrics, and dataset sources. We used a predefined data extraction form to ensure consistency across the studies. Figure 1 provides a detailed description of these steps.

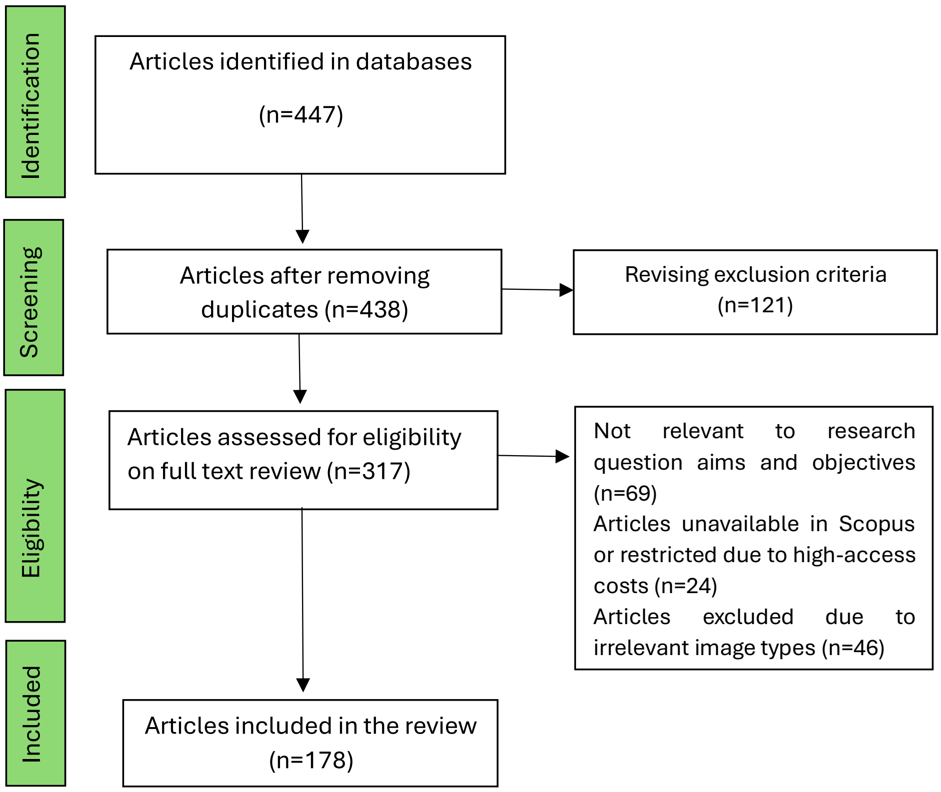

Figure 1. PRISMA flow diagram illustrating the process of identifying, screening, and selecting articles from various databases, culminating in the inclusion of articles for the review.

3. Results

In this section, we present the findings of our systematic review of the literature on machine learning applications in crop pest and disease detection. We gathered data from selected studies and synthesized the information, focusing on the types of machine learning models used, their performance metrics, and the specific crops and diseases they target. We also discuss the sources of the datasets and the various machine learning algorithms, including deep learning models such as CNNs and their effectiveness in diagnosing plant health issues. In addition, the results highlight the common challenges faced by current technologies and the innovative solutions proposed by researchers to overcome these obstacles.

3.1. Observe Methodology in Analyzed Papers

While reviewing the papers for this systematic review, it became apparent that the methodology commonly employed includes traditional preprocessing steps, such as segmentation and feature extraction, which are essential for preparing data before they are fed into machine learning models. Traditionally, these steps involve manually segmenting images to isolate regions of interest and extracting specific features that are most relevant to the task at hand. This process ensures that the data are in the optimal state for model training, which leads to improved accuracy and reliability.

However, with the advent of deep learning models, particularly CNNs, the approach to segmentation and feature extraction has evolved. CNNs inherently perform these tasks as part of their architecture, where the convolutional layers automatically learn to identify and extract features from raw input data. This automation reduces the need for manual intervention and allows for the discovery of complex patterns that might not be easily captured using traditional methods. With the integration of traditional preprocessing techniques into CNNs, the models can learn effectively even with fewer data. This allows for the efficient utilization of the available data and enhances the learning capabilities of the CNNs. The constructed methodology consisted of five main stages: data acquisition, preprocessing, segmentation, feature extraction, and prediction. These stages were consistently applied across various domains and applications, highlighting their importance in the research landscape.

Figure 2 captures the essential steps of the core methodology used throughout the reviewed literature, providing an overview of the research process and highlighting the systematic approach adopted by researchers.

Figure 2. Flow diagram depicting the stages of data processing in the reviewed literature, including data acquisition, preprocessing, segmentation, feature extraction, and prediction/results. Each step is crucial for thorough data analysis and interpretation in various research domains.

Data acquisition: In this stage, researchers collect data from various sources that are relevant to their respective fields of study, including repositories, experimental setups, and real-world scenarios. This stage requires meticulous planning to ensure the quality, relevance, and integrity of the collected data, which serves as the foundation for subsequent analysis.

Preprocessing: After collecting data, the preprocessing step refines and prepares the raw data for further analysis. This phase involves techniques such as noise reduction, data cleaning, normalization, and outlier removal to handle inconsistencies and improve the quality of the dataset, allowing for more robust and reliable analysis in subsequent stages.

Segmentation: Researchers applied segmentation algorithms to partition the preprocessed data into meaningful segments or regions of interest. This process facilitates the isolation of relevant features within the data for subsequent analysis and interpretation.

Feature extraction: During feature extraction, the researchers aimed to identify and extract discriminative features from the segmented data. This stage involved the application of various algorithms and techniques to characterize the salient aspects of the dataset, such as the texture, shape, color, or spectral properties, for subsequent analysis and decision making.

Prediction/results: The final stage of prediction included the use of machine learning algorithms, statistical models, or predictive analytics techniques to infer insights or make informed predictions based on the extracted features. The researchers used the extracted features as input variables to train and evaluate predictive models, enabling tasks such as classification, regression, anomaly detection, or forecasting.

3.2. Distribution of Dataset Sources

The datasets utilized in the analyzed works were sourced from a variety of repositories and platforms summarized below and illustrated in Figure 3. Some of the reviewed papers used combinations of multiple datasets. Analyzing the frequency with which they were used provides insight into the strengths and weaknesses of each model.

Plant Village [18]: Fifty-five papers used the Plant Village repository. This repository serves as a comprehensive resource for plant disease images, providing researchers with access to a diverse collection of annotated data.

Self-created: A substantial portion of the authors, comprising thirty entries, used self-created datasets. The researchers collected and curated their datasets through experimental setups, field observations, or data collection efforts tailored to their specific research objectives.

Other: Twenty-two of them were from other miscellaneous datasets not explicitly mentioned above. These sources include proprietary datasets, datasets obtained from collaborators or institutions, or datasets sourced from other specialized repositories.

Kaggle: six of them used a dataset from the Kaggle repository, an online platform well known to provide a wide variety of datasets [19].

UCI (University of California, Irvine) Machine Learning repository [20]: Five used the UCI Machine Learning repository, a famous repository for machine learning datasets. These datasets are often utilized for benchmarking and experimentation in machine learning research.

Google Repository: two of them used a dataset from the Google repository, indicating the utilization of publicly available datasets or images accessible through Google's platforms.

Mendeley: six of them used a dataset from the Mendeley repository, which provides a platform for collaboration and ensures data accessibility [21].

The distribution of data sources provides information on the diversity and breadth of the data used in this analysis. The following graph visualizes the distribution of dataset sources.

3.3. Analyzed Crops

The research papers cover an extensive range of plant species, including common agricultural staples such as apples, corn, grapes, potatoes, and tomatoes. In addition, it explores more specialized crops like cassava and groundnut. The breadth of plant species under investigation is extensive. In addition, the articles explore various fruits, such as peaches and strawberries, showcasing the diversity of botanical specimens examined in the literature. The analysis also extends to trees such as pine and American elm, as well as ornamental plants such as sunflowers and barbary wolfberries, contributing to the diverse array of botanical topics explored in the research papers. The distribution of the different plants found in this review is illustrated in Figure 4.

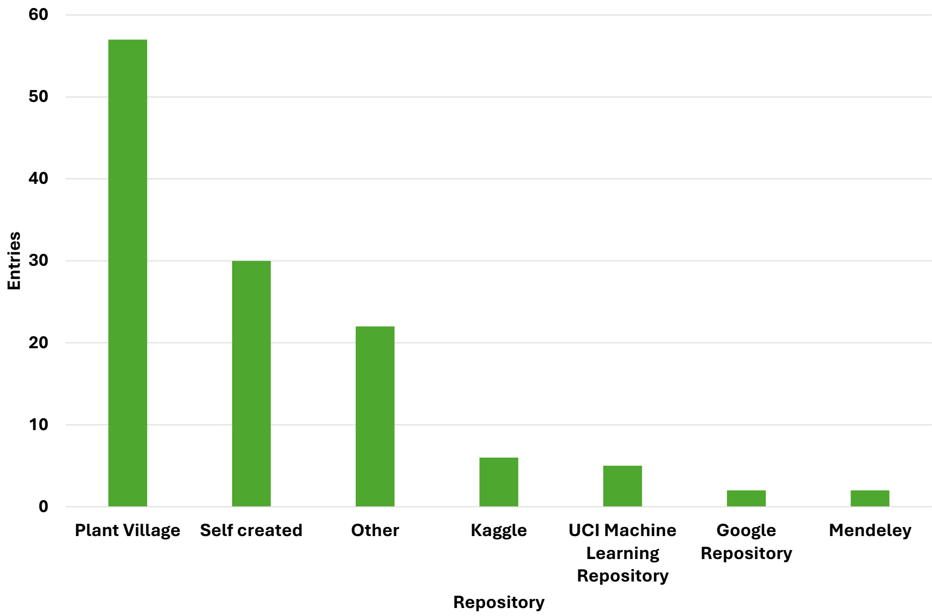

Figure 3. Distribution of dataset sources utilized in this study, illustrating the number of entries from various repositories and platforms.

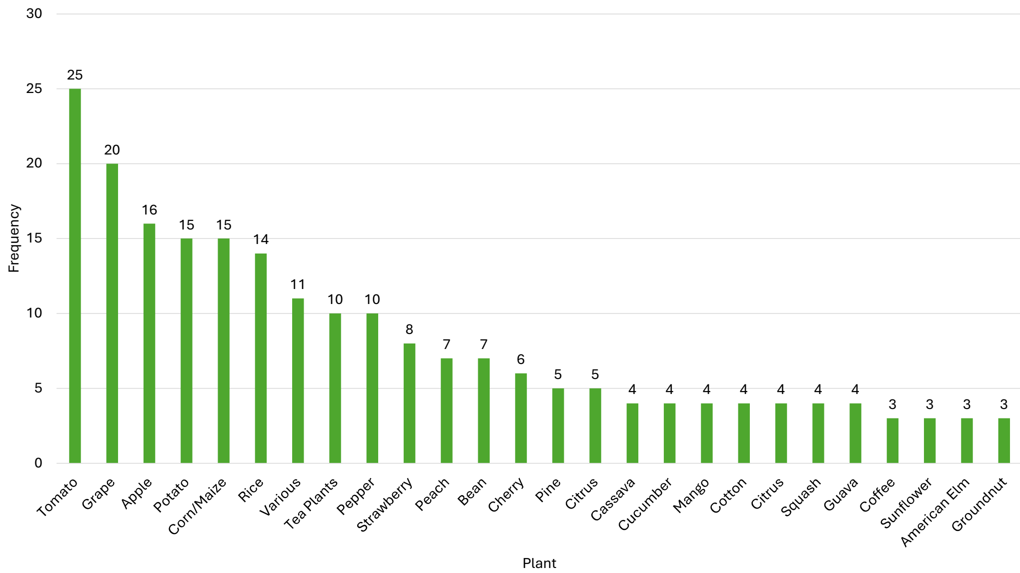

Figure 4. Frequency of plant species mentioned in the analyzed papers for leaf analysis. The chart lists the species in descending order of citation frequency, indicating the research focus on various plants.

3.4. Crop Diseases

The articles analyzed covered a diverse range of plant diseases and pests affecting a wide range of crops and plant species. Diseases such as Powdery mildew, Downy mildew, Black root, early blight, Common rust, and Leaf Spot disease were frequently discussed, indicating their importance in agricultural research and plant pathology. In addition, various leaf diseases were common topics of investigation. Figure 5 shows the frequency of the diseases found in our analysis, and Figure 6 illustrates the relationships between plant species and their associated diseases. In this diagram, the central nodes represent the plant diseases, while each node at the end of a connection represents a specific plant species. The size of the disease nodes correlates with the number of plant species affected, indicating the prevalence and spread of these diseases among different plant species.

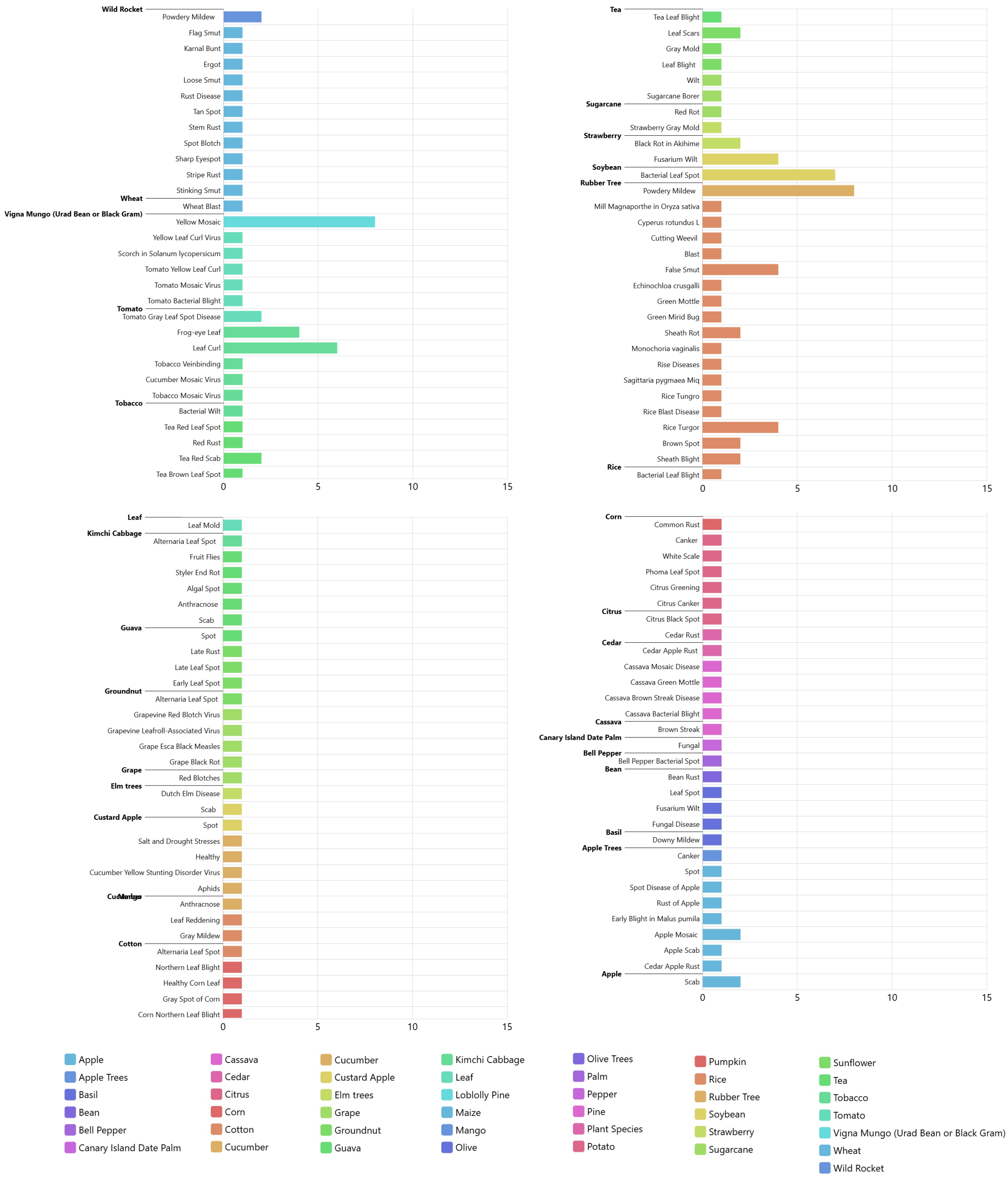

Figure 5. Frequency of occurrence of plant diseases and pests in analyzed articles. The chart shows the prevalence of various plant diseases and pests as mentioned in the analyzed literature. Notably, diseases such as Yellow Mosaic, Leaf Curl, Bacterial Leaf Spot, and Powdery mildew were commonly cited, highlighting their value in agricultural research and plant pathology.

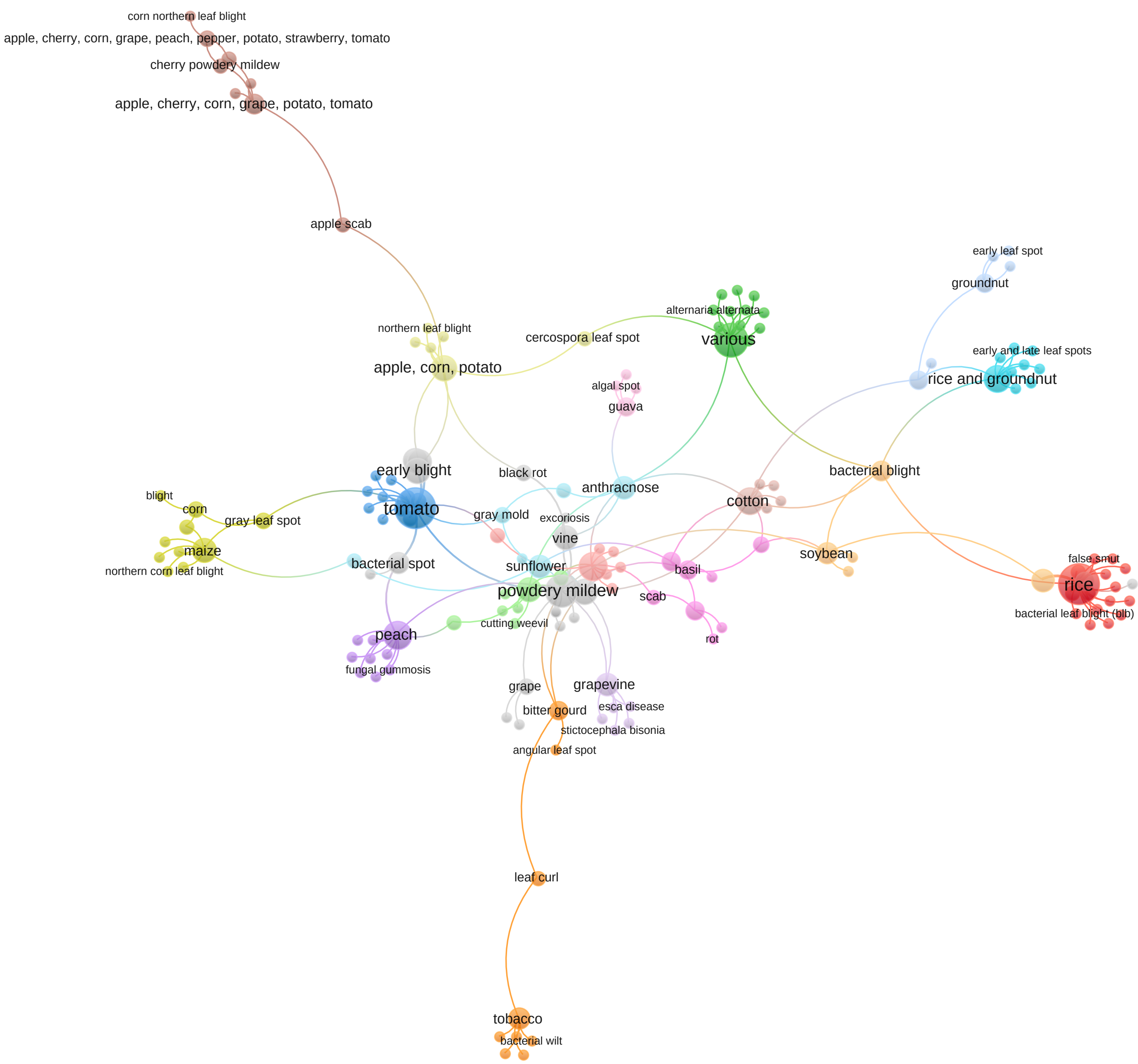

Figure 6. Network diagram illustrating the relationships between plant species and their associated diseases. In this diagram, each node at the end of a connection represents a specific plant species, while the nodes at the center represent various plant diseases. The lines connecting the plant species to the central nodes depict the susceptibility of each plant to the associated diseases. The size of the disease nodes correlates with the number of plant species they affect, indicating the prevalence and spread of these diseases across different plant species.

3.5. Deep Learning Models

This section categorizes and describes different architectures and their adaptations for the detection of pests and diseases in crops. It highlights CNN architectures such as Inception, MobileNet, and ResNet, among others. We explore how these models have been applied, the specific advances they have made to the field, and their performance metrics.

3.5.1. CNN and Variants (InceptionV3, MobileNet, ResNet, and Others)

Table 1 shows a list of works that highlight the model used along with its reported metrics.

Table 1. Overview of CNN architectures and their performance metrics in disease detection for various plant species. The table includes details on precision, recall, F1 score, and accuracy for each model.

Author	Model Name	Precision	Recall	F1	Accuracy
[22]	ResNet-9	99.67	99.33	99.33	99.25
[23]	3D CNN	95.18	94.86	94.97	99.04
[24]	VGG16 m	94.32	89.26	91.72	91.93
[25]	R-CNN with VGG-16 RF	99.94	99.64	99.91	97.30
[26]	GoogLeNet-RESNET	94.00	95.00	95.00	99.08
[27]	NN	93.00	78.00	77.00	98.00
[28]	CNN	92.30	90.10	91.20	93.50
[29]	CNN and VGGNet-16	87.60	70.00	-	100.00
[30]	ResNet-50	98.00	98.00	98.00	98.25
[31]	CNN	89.00	98.00	93.00	92.50
[32]	CNN	88.00	82.00	85.00	87.90
[33]	YOLOv5	98.30	97.80	96.00	-
[34]	EfficientNet B0	88.00	87.00	93.00	98.85
[35]	DeepLabV3+ResNet50	75.70	72.20	74.20	99.70
[36]	AdaBoostSVM	95.00	94.90	94.00	98.80
[37]	WD2CNN	98.83	97.82	98.41	98.72
[38]	EffiNet-TS	99.00	99.00	98.89	99.00
[39]	DCDM + CNN	93.38	97.98	98.17	98.78
[40]	RDTNet	99.55	99.53	99.54	99.53
[41]	RSODL-PDDC	97.58	97.57	97.57	98.78
[42]	DnCNN	85.00	83.00	96.83	97.91
[43]	MobileNet	84.00	79.00	75.80	-
[44]	ResNet 50s	99.50	-	99.70	99.75
[45]	MResNet	-	99.47	-	99.62
[46]	EfficientNet	-	97.00	-	89.00
[47]	Modified CNN	99.81	-	71.53	-
[48]	Inception-ResNet-V2	98.96	98.38	-	99.10
[49]	EfficientNetv2-S	-	-	92.88	-
[50]	GPR-CNN	99.10	98.29	99.13	99.17
[51]	CNN	-	-	-	-
[52]	DLPDS	100	100	99.70	99.95
[53]	CNN	96.81	96.86	96.78	96.86
[54]	CNN	99.27	99.44	99.28	97.59
[55]	ResNeXt	99.40	99.20	99.20	98.92
[56]	LC3Net	89.12	89.00	89.00	92.29
[57]	RFBDB-GAN	73.20	69.60	71.40	-
[58]	AISDLT	99.62	99.53	99.57	98.00
[59]	CNN with ResNet50	95.83	91.67	88.93	94.67
[60]	CNN	96.60	96.50	-	96.00
[61]	CRUNet	92.27	92.37	92.32	92.48
[62]	StrawberryTalk	95.00	100	-	92.37
[63]	IRNN-TL	93.71	-	-	96.70
[64]	TeenyNet	97.44	97.47	97.42	98.94
[65]	DCNN	-	-	97.00	98.92
[66]	DCNN	95.49	95.47	95.41	95.04
[67]	DCNN	87.20	68.00	76.40	-
[68]	MobileNetv2-YOLOv3	91.32	-	93.24	-
[69]	Yolov3, VIs and NDTIs	-	91.81	-	94.77
[70]	CAE and CNN	98.00	98.72	98.36	98.38
[71]	dCNN	99.82	99.82	99.82	99.81

Models such as ResNet-9 and 3D CNN stand out with high metrics results. ResNet-9's residual connections allow for deeper networks and better feature reuse, ensuring a robust model. In contrast, 3D CNN offers the advantage of processing 3D structures, which could benefit projects that require spatial analysis. The R-CNN with VGG-16 RF, though its complexity, could pose challenges in terms of computational power. In general, ResNet-9 and GoogLeNet-ResNet offer a balance between complexity and precision, making them versatile for most plant disease detection tasks.

Table 2 continues the list of works that describe the model used along with the accuracy reported. The table provides details on various approaches, ranging from CNNs to combined mechanisms and classifiers.

Table 2. Summary of models utilized for crop disease detection and classification, featuring model names along with their reported accuracy.

Author	Model Name	Accuracy
[72–84]	CNN	99.53, 99.24, 99.00, 99.00, 98.75, 98.01, 96.46, 94.00, 93.00, 91.25, 89.00, 70.00, 99.00
[85]	CNN with HCF	99.93
[86]	CNN and SVM	97.20
[87]	CNN with RF	98.63
[88]	CNN with NCA	99.50
[89]	CNN with S-CNN	98.60
[90]	E-CNN	98.17
[91]	HCO-CNN	98.06
[92]	MSA-CNN	98.44
[93]	PDDCNN	99.75
[94]	ResNet50	94.29
[95]	Yolov4	95.00
[96]	CCA-YOLO	90.15
[97]	DLMC-Net	99.50
[98]	K-means and ANN	97.90
[99]	Yellow-Rust-Xception	97.90
[100]	ML with ELM, SVM, and KNN	96.67
[101]	SE-VRNet	99.00
[102]	CNN	97.04
[103]	CenterNet	73.30
[104]	YOLOv5	93.00
[105]	RiceNet	99.03
[106]	SegNet	99.24
[107]	Few-shot-learning-based	93.19
[108]	WeedDet	94.10
[109]	BoVW	70.08
[110]	Conv-3 DCNN	98.00
[111]	LTriTP	97.80
[112]	M-Net	71.00
[113]	MobileNetV2	97.70
[114]	MobileNetV3	93.23
[115]	ANN	99.67
[116]	PeachNet	94.00
[117]	VirLeafNet	91.23
[118]	1D-ResNet	91.00
[119]	Inception V3	95.60
[120]	CoDet	96.00
[121]	DV-PSO-Net	94.72
[122]	FCDCNN	98.00
[123]	Sentinel-2	88.26
[124]	DbneAlexNet	94.70
[125]	VGG16	93.00
[126]	PMF+FA and ResNet50	90.12
[127]	Gabor CapsNet	98.13
[128]	ResNet-101	99.00
[129]	Unet	96.09
[130]	MDSCIRNet	99.33
[131]	YOLOv5	92.00
[132]	DCNN with Confusion Matrix	93.00
[133]	ODCNN	99.22
[134]	DCNN	96.46

Ref. [135] reports a precision of 97.81 in their Android app with the machine learning model that helps to identify mango disease. On the other hand, the works from [136–138] exhibit metrics not mentioned in the present review, such as R and R^2, among others.

Models like EfficientNet B0 and DeepLabV3+ResNet50 deliver a balanced performance with less memory use, making them ideal for edge devices with limited resources. YOLOv5, though slightly less accurate, excels in real-time detection, crucial for time-sensitive tasks such as crop monitoring. Table 2 shows how different CNN variants suit varying needs for precision, speed, or resource efficiency.

3.5.2. Hybrid Models (CNN with SVM and Others Combinations)

The development and evaluation of hybrid machine learning models in disease detection in agriculture involve the integration of CNN with other machine learning techniques such as an SVM and long short-term memory networks (LSTM). Table 3 provides an overview of various hybrid models and their performance metrics.

Table 3. Hybrid Convolutional Neural Network models combined with other machine learning techniques showcasing precision, recall, F1 score, and accuracy metrics.

Author	Model Name	Precision	Recall	F1 Score	Accuracy
[139]	I-LDD	93.34	93.19	93.06	93.22
[140]	RDODL-APDC	95.83	95.85	95.82	95.80
[141]	K-Means and SVM	99.50	99.50	-	99.05
[142]	PWDNet	85.90	94.10	-	93.20
[143]	CNN-LSTM	-	95.11	-	95.11
[144]	HXTL-COKELM	-	94.10	98.50	98.90
[145]	DCGAN	-	-	-	96.90
[146]	ConLSTM-U-Net	-	-	-	85.00
[147]	MobileNetv2 + SVM	-	-	-	99.00
[148]	LeIAP	96.82	96.82	96.82	95.00
[149]	FA-SVM	92.00	90.73	-	91.30
[150]	ANN with HOG	-	-	99.00	99.24
[151]	MSSOA	-	-	-	91.00
[152]	RF with 3D-CNN	-	-	-	87.00
[153]	KNN, ANN	98.00	88.00	97.00	99.00
[154]	ResNet with SVM	-	-	-	97.86
[155]	SVM	-	-	-	80.00
[156]	RCNN + SVM	-	-	-	77.00
[157]	SVM, PLS-DA, and ResNet18	90.16	-	-	-
[158]	ResNet-50 + SVM	80.38	73.02	74.32	90.60
[159]	CNN + SVM	85.71	85.71	84.86	95.39
[160]	CNN-RF	96.00	93.00	93.00	98.00
[161]	CNN+SVM	-	-	-	95.02
[162]	Bat-BCDPBM	100	98.18	98.84	98.60
[163]	GLCM with RF	98.77	98.48	98.62	98.62
[164]	SMbRF	98.76	99.52	98.12	99.29
[165]	CNN, SVM, DT, NB, and RF combination	-	-	-	99.20
[166]	SVM, KNN, and NB	-	-	-	82.00
[167]	KNN	-	-	-	98.00

Ref. [168] proposed an SVM optimized by a genetic algorithm and particle swarm optimization that reported an R^2 of 0.98 and an MSE of 0.2, and ref. [169] presented an SVM with a polynomial kernel function and PCA with a recognition rate of 97 3%. Ref. [170] presents a table that provides a mean ranking of their proposed model in different datasets of plant diseases but does not provide any metric value observed in this review.

Hybrid models that combine CNNs with other classifiers, such as an SVM, generally perform well in both precision and recall, with the I-LDD model achieving a solid balance between metrics. Hybrid models, such as CNN-LSTM, integrate temporal learning capabilities, making them well-suited for analyzing disease progression over time. Although slightly more complex than standalone CNN models, hybrid approaches offer a flexible alternative that could be tailored to specific use cases, such as long-term disease management in crops.

3.6. Machine Learning Models

In this section, we explore the application of traditional machine learning models in the field of agriculture, specifically focusing on the detection and management of diseases in various crops. Unlike deep learning models, these traditional approaches often employ statistical, geometrical, or rule-based techniques to process and analyze data. The models vary widely in complexity and application, from basic logistic regression to ensemble methods that integrate multiple learning algorithms for improved prediction accuracy. Table 4 summarizes some of these traditional models, presenting their precision, recall, F1 score, and overall accuracy in specific agricultural applications.

Table 4. Traditional machine learning models and their performance metrics in agricultural disease detection, showcasing a range of approaches from simple regression to complex ensemble models.

Author	Model Name	Precision	Recall	F1	Accuracy
[171]	Mask R-CNN	89.00	91.00	87.00	83.00
[62]	IoT-based	95.00	100.00	-	96.88
[172]	RF, SVM, and KNN	-	-	-	90.70
[173]	SSAFS	-	-	-	83.38
[174]	CNN	-	-	-	85.00
[175]	LR	85.35	85.00	85.15	85.00
[176]	VOCs	-	-	-	94.00
[177]	SVM	-	-	-	99.90
[178]	LDA	93.00	-	-	-
[179]	SVM	-	-	-	95.23
[180]	C-SVM and Fine-KNN	-	-	-	98.00
[181]	PLS-LDA	-	-	-	85.00
[182]	grained-GAN	-	-	96.27	-
[183]	SVM and KNN	-	-	-	**100**
[184]	ML with fused HOG	89.00	89.00	89.00	89.11
[185]	DNN with CSA and k-means	95.92	96.41	-	96.96
[186]	SVM	-	-	-	98.38
[141]	SVM	99.50	99.50	-	99.05
[187]	XGBoost + KNN	95.00	98.00	-	98.77
[171]	RF	95.00	92.00	92.00	97.00
[188]	SVM	90.60	91.50	85.30	90.20
[189]	BEiT	**98.00**	97.00	97.00	98.20
[190]	SLIC	-	-	-	99.38
[139]	I-LDD with ELM	93.34	93.19	93.06	93.22
[191]	SVM	-	-	-	91.25
[111]	LTriTP with T-HOG	97.98	97.77	97.83	97.80
[192]	EKNN	-	-	-	99.86
[193]	RM-SVM	-	-	-	95.60

The remaining authors who do not appear in this section's tables are ref. [194], who reported a precision of 95.80 in their unbiased teacher v2 semi-supervised object detection DCNN model; ref. [195], who exhibited an $R^2 > 0.7$ in their Botrytis risk algorithm; and ref. [196], whose machine-learning-based model reduced nonphotochemical quenching and increased quantum PSII yield (ΦPSII) compared to the leaf areas nearby.

Traditional machine learning models, as shown in Table 4, provide simplicity and ease of implementation. Models such as Random Forest and SVMs continue to hold their ground, especially when dealing with smaller datasets or less complex tasks. For projects with limited resources or smaller datasets, Random Forest offers a straightforward yet effective solution. However, the accuracy of Mask R-CNN and LDA suggests that traditional models are gradually being outpaced by CNN and hybrid architectures in terms of performance.

3.7. Preprocessing

Our analysis found a wide range of preprocessing techniques applied to different types of data, such as images, spectral images, and fluorescence kinetics curves. This diversity suggests that researchers and practitioners use various methods to prepare their data for analysis or further processing. Some preprocessing combinations involve advanced techniques, such as segmentation algorithms, feature extraction methods, and background removal using sophisticated models such as Mask RCNN or RetinaNet. This indicates a level of sophistication and specialization in data preprocessing to address specific challenges or requirements. The diversity of preprocessing techniques implies that researchers are actively experimenting with different methods and potentially exploring innovative approaches to prepare their data. This experimentation could lead to the development of novel preprocessing pipelines optimized for specific applications or domains.

Figure 7 shows the distribution of the preprocessing techniques identified in the reviewed literature. Among the various methods used, resizing appears to be the most frequently utilized technique, followed by noise reduction. Additionally, normalization and image enhancement are equally mentioned, and other preprocessing methods are mentioned, although with lesser frequency.

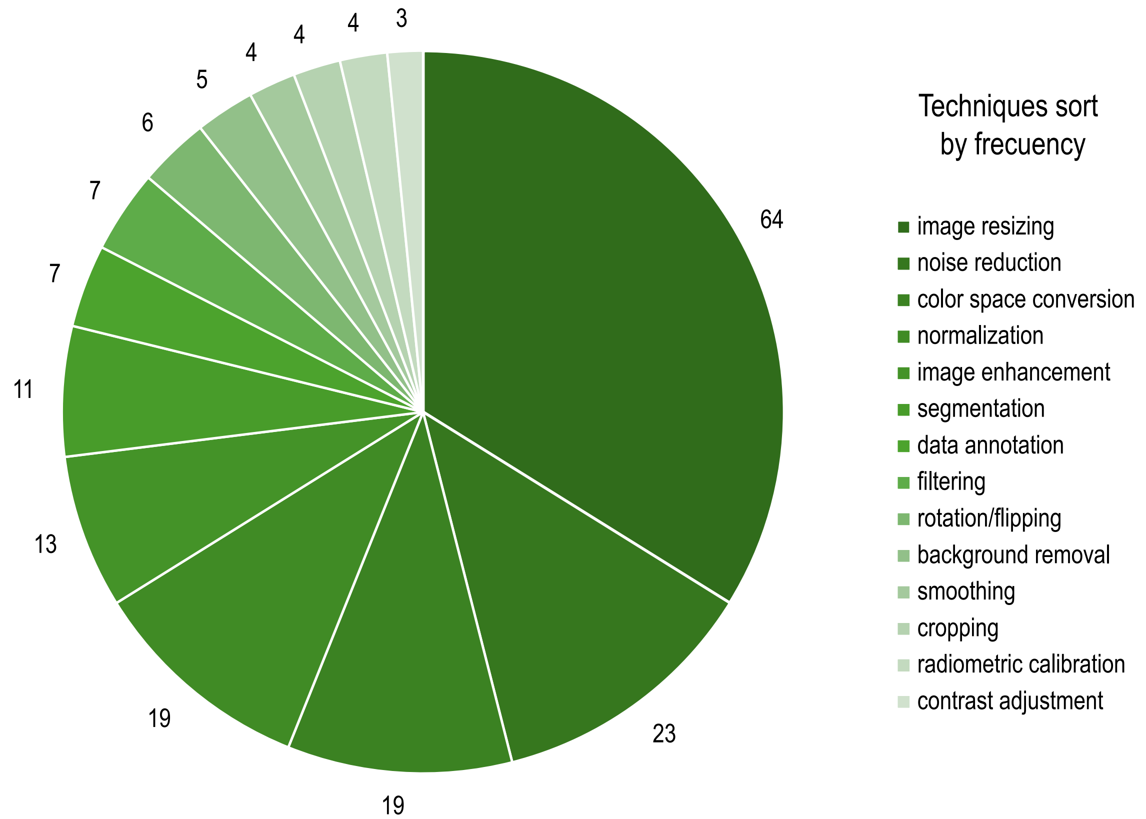

Figure 7. Distribution of preprocessing techniques used in the literature. The pie chart illustrates the frequency of various preprocessing methods, such as resizing, noise reduction, color space conversion, normalization, enhancement, segmentation, and others, such as annotation filtering and rotation or flipping and more, with the number of papers employing each technique.

3.8. Data Augmentation

Data augmentation plays a vital role in machine learning, particularly in the domain of image processing. Data augmentation methods increase the diversity of data available for training models by artificially enhancing training datasets through various transformations, thereby improving their robustness and ability to generalize from limited input. Standard techniques include rotating, flipping, and custom-made, as well as more complex modifications, such as synthetic image creation or adding noise. These strategies are designed to simulate real-world variations and introduce more scenarios for the model to learn from.

In our analysis, rotation and flipping images are the most common data augmentation techniques. Zooming, resizing, and brightness enhancement are frequently mentioned, as well as scaling and noise addition, followed by inversion and color improvement. Figure 8 shows the frequency of the different augmentation techniques found in the review.

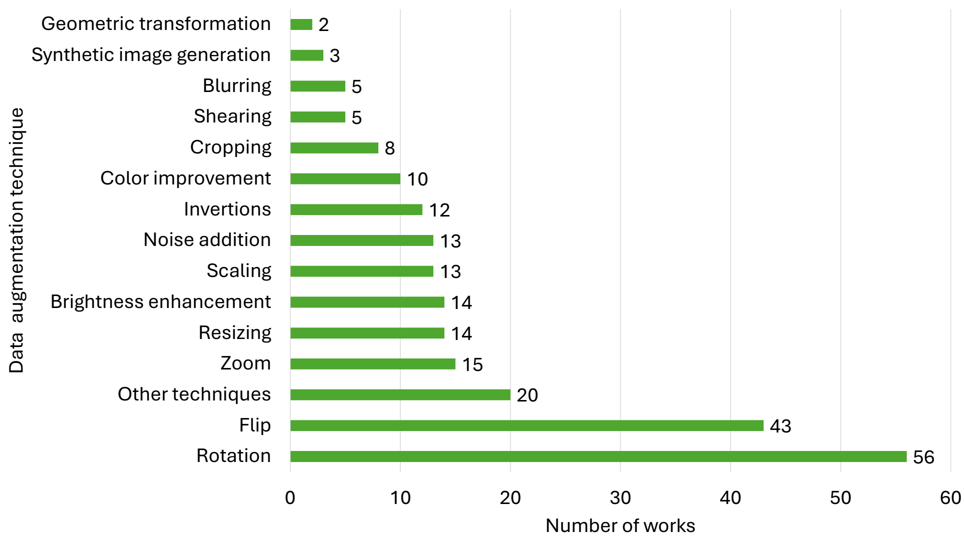

Figure 8. Frequency of various data augmentation techniques used in literature. The bar chart quantifies the implementation of techniques such as geometric transformations, blurring, and synthetic image generation.

Other data augmentation techniques, such as bootstrap resampling, image inversion, gamma correction neural style transfer, generative adversarial network, position augmentation, balance mix-up, label shuffling, synthetic backgrounds, conditional generative adversarial networks, and principal component analysis, were also mentioned.

3.9. Features

In classic machine learning methods, the selection and use of features critically influence the performance of the models.

The noticeable frequency of various characteristics reveals valuable information on the predominant characteristics considered in the research landscape (see Figure 9). Color was found to be the most analyzed feature, followed by texture. Shape descriptors were also prevalent, highlighting the importance of geometric characteristics in characterizing the data. Further investigation revealed specific feature extraction techniques utilized within the analyzed literature. High-level features obtained through CNNs and spectral information were also widely mentioned. The Gray-Level Co-Occurrence Matrix (GLCM) is also relevant in capturing spatial dependencies within images. Similarly, local binary patterns (LBPs) and energy, which describe local changes in the quality of images, were also observed. Our analysis revealed a subset of features that, although mentioned less frequently, possess unique characteristics with significant practical implications. These features include standard deviation local binary patterns (LBPs), correlation homogeneity, bounding boxes, and edges. They stress their relevance in specialized applications such as remote sensing and environmental monitoring, making research more applicable and impactful.

Furthermore, our comparison between singular and multi-mentioned features revealed intriguing patterns. Features such as color, texture, and shape consistently stood out in both categories, affirming their universal significance in machine learning.

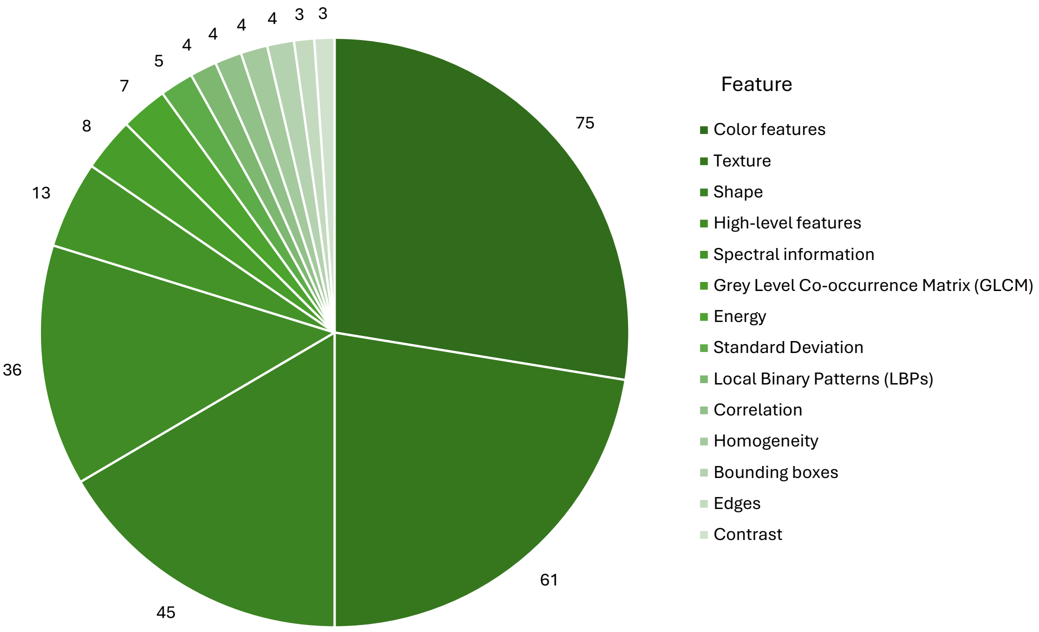

Figure 9. Distribution of frequently mentioned features in the literature. The chart categorizes and quantifies the occurrence of different features such as color, texture, and shape, highlighting their significance and prevalence in feature extraction when used with machine learning methods.

3.10. Comparative of Related Works

This review builds upon previous studies by providing a comprehensive and up-to-date perspective on the use of machine learning for plant disease and pest detection. Furthermore, the period 2019 to 2024 serves as a continuation of previous work reported in the state of the art, building on and complementing earlier reviews. Table 5 helps to contextualize the scope and contributions of our review within the broader research landscape, showing how our study addresses gaps and complements previous works.

Table 5. Comparison of this work against state-of-the-art reviews.

Work	Plants	Datasets	Diseases	Model Name	Metrics	Data Augmentation	Preprocessing	Extracted Features	Model Proposing	Period Search
Doutoum and Tugrul [13]	X	X		X	X		X	X		2006–2022
Mekha and Parthasarathy [16]				X	X					2009–2021
Mohan et al. [12]			X	X	X		X			2011–2022
Bondre and Patil [14]	X	X	X				X	X		2012–2022
Kini et al. [15]				X	X		X	X		2015–2021
Jackulin and Murugavalli [11]				X	X					2020–2022
Our work	X	X	X	X	X	X	X	X	X	2019–2024

This systematic review not only addresses this recent period but also includes a thorough analysis of various critical aspects such as plant datasets, diseases, model names, metrics, data augmentation, preprocessing techniques, extracted features, and model propositions. By focusing on these elements, we aim to provide a comprehensive and up-to-date analysis that leverages the latest tools and datasets available. This holistic approach improves the relevance and impact of our findings in the fast-evolving field of agricultural technology while ensuring a more contemporary analysis of recent methodologies and datasets.

Previous reviews, like [13,16], have focused on various aspects of plant disease detection using machine learning and deep learning techniques. This review, on the other hand, explicitly addresses recent advancements from 2019 to 2024, providing a more up-to-date analysis and including newer methodologies and datasets, as well as [11,15], who address only preprocessing or augmentation techniques in limited contexts. Furthermore, we highlight the integration of data augmentation and preprocessing techniques and detail exclusion criteria, inclusion criteria, and focus on hybrid model development, which earlier reviews have not thoroughly explored or were less emphasized in earlier works. This makes this work relevant for addressing challenges such as handling unstructured image datasets and improving model generalizability. Table 6 shows a summary of reported work related to plant disease detection.

Table 6. Comparison of plant disease detection studies.

Author	Techniques Used	Diseases Covered	Papers Reviewed	Performance Metrics	Challenges Addressed
[11]	ML and DL techniques for plant disease detection	Various	60	Various metrics	Research gaps in DL techniques
[12]	ML and DL techniques	Various	64	Performance metrics	Research gaps and challenges
[13]	CNN for leaf disease detection	Leaf diseases	256	CNN performance	Data representation, labeling, collection, overfitting, dataset inadequacy
[16]	AI techniques for pest identification	Pest infestations	17	Accuracy values	
[14]	DL strategies, CNN models	Various	80	CNN performance	Handling unstructured images, dataset needs
[15]	Segmentation, ML classifiers, DNNs	Various	36	Accuracy	Complex backgrounds, data inadequacy
Our work	ML and DL techniques for plant disease detection	Various	82	Various metrics	Handling unstructured images, dataset needs

In contrast with [12], who reviewed 64 papers, or [15], who reviewed 36, this review considers a broader range of studies, enabling a deeper understanding of the trends and advancements in plant disease detection using machine learning and deep learning techniques and addressing challenges that were only partially explored in prior works, such as data representation [13] and data inadequacies [15]. Our study provides specific solutions to these challenges, such as incorporating data augmentation techniques (including rotation, scaling, and noise addition) to tackle dataset variability besides exploring hybrid models, like CNN-SVM combinations, to improve robustness and address issues related to unstructured images. With these methodological advances, a more comprehensive approach was ensured to overcome challenges in plant disease detection.

4. Discussion

This section interprets the results, discusses common models for pest and disease detection in crops, reviews related work, and compares the current study with previous reviews.

This systematic review delves into the application of deep learning methods and data augmentation techniques in plant disease detection. Deep learning, mainly through CNNs, has been an effective tool for identifying and classifying plant diseases from image data. Our review highlights the effectiveness of various CNN architectures, including Inception, MobileNet, and ResNet, which have been adapted to address the complexities of disease detection in crops. These models demonstrate high accuracy and precision in detecting a variety of plant diseases, making them essential in modern agricultural practices. Although these models have advanced significantly, challenges such as overfitting and data representation remain, particularly when dealing with limited or imbalanced datasets. The use of transfer learning and hybrid models, combining CNNs with other machine learning techniques such as an SVM, showed further improvement in model performance and generalizability. Data augmentation plays a vital role in improving the robustness and accuracy of deep learning models. By artificially expanding training datasets through various transformations such as rotation, flipping, resizing, and adding noise, we found that rotation and flipping were the most widely used augmentation techniques, followed by other methods such as brightness enhancement and geometric transformations. These techniques are helpful in scenarios where obtaining a large and diverse dataset is challenging, as they help simulate real-world variations and introduce additional scenarios for the models to learn from. In general, the integration of deep learning with data augmentation strategies is shown to significantly enhance the ability of models to detect and diagnose plant diseases accurately, thus contributing to more sustainable and efficient agricultural practices.

In the context of pest and disease detection in crops, selecting the most suitable model architecture is critical to achieve accurate and reliable results. Our systematic review of the relevant literature suggests that CNN variants, particularly ResNet and InceptionV3, stand out as preferred choices due to their effectiveness in handling the complexities of image classification tasks inherent in agricultural pathology. ResNet, with its residual connections, allows deeper networks to be trained to address the challenges posed by the classification of complex disease symptoms. Similarly, InceptionV3's architecture exhibits robust adaptability to recognizing patterns characterized by extreme variability, a common occurrence in plant disease symptoms. Our analysis highlights common datasets, with the Plant Village dataset appearing as a common choice among researchers for evaluating machine learning models.

The reviewed detection techniques have benefited from using transfer learning techniques. According to [197], these techniques report at least 93% precision by using little training data and adequately tuning the pre-trained model. In the work of [198], they improved a VGGNet to detect plant diseases up to 92% with images with complex backgrounds. In [199], they observed that a base YOLOv4 model performs poorly when trying to classify the disease in a single leaf. To improve the accuracy, they modified the architecture by adding the spatial pyramid pooling block, with which they achieved an accuracy of up to 95.9%. Another alternative solution to disease detection is the use of hybrid techniques. In [200], the authors implemented a TomSevNet as an inception layer in a CNN algorithm by considering 30 different classes with an accuracy of 96.91%. The work of [170] shows the performance of a model that integrates machine and deep learning in a work environment with Optuna. They demonstrated that these techniques can achieve an accuracy of at least 87.5% by testing with a public dataset for tomato early blight disease. In [70], they implemented a Convolutional Autoencoder network with a CNN for the detection of bacteria in peach crops, obtaining an accuracy of 98.38%. In addition, they report that the model presents a significant reduction in plant detection compared to the reported model because a significant amount was not required in the training stage.

Crop-specific models enhance accuracy by reducing false positives but need extensive, specialized datasets. These models depend on large, diverse crop-specific datasets, which are complex and resource-intensive to acquire [201,202]. A major limitation is their lack of generalizability, requiring retraining for each crop and increasing complexity and cost. They also struggle to adapt to new diseases or environmental changes, necessitating continuous updates to maintain accuracy. This highlights the need for models that handle environmental variability and can generalize across conditions.

Table 7 provides a comparative overview of key machine learning and deep learning models, describing their characteristics to help readers select the right models. The analysis also identifies areas for improvement, such as developing resilient models that adapt across crops and types of disease for more practical and scalable agricultural disease management.

Table 7 analyzes machine learning and deep learning models. ResNet and VGG excel in complex image classification. MobileNet and EfficientNet are efficient on resource-limited devices. YOLOv5 is ideal for real-time detection. Traditional models like SVMs and Random Forest are suitable for smaller datasets but are usually less accurate than deep learning models.

Figure 10 summarizes the accuracy ranges of the models reviewed for the detection of plant disease. The horizontal bars illustrate the performance variability across different datasets and experimental setups as reported in the literature. Models such as ResNet and YOLO consistently demonstrate high accuracy across datasets, while DeepLab exhibits more variability, highlighting the challenges faced in specific tasks like segmentation.

Table 7. Comparative analysis of machine learning and deep learning models for plant disease detection.

Model	High Accuracy Needed	Low Computational Resources	Real-Time Detection	Large Datasets	Small Datasets	Generalize to New Crops	Complex or Hybrid Decision Boundaries
ResNet [22,26,35,44,45]	X	-	-	X	-	X	X
MobileNet [43,147]	X	X	X	X	X	X	-
EfficientNet [34,38,94,170]	X	X	X	X	X	X	-
CNN-SVM [86]	X	-	-	X	X	X	X
VGG [24,25,29,44,133]	X	-	-	X	X	X	X
YOLO [33,62,95,96,104,136]	X	X	X	X	X	X	X
Inception [41,44,45]	X	X	X	X	X	X	X
Mask R-CNN [24]	X	-	X	X	X	X	X
DeepLab [35]	X	X	X	X	X	X	-

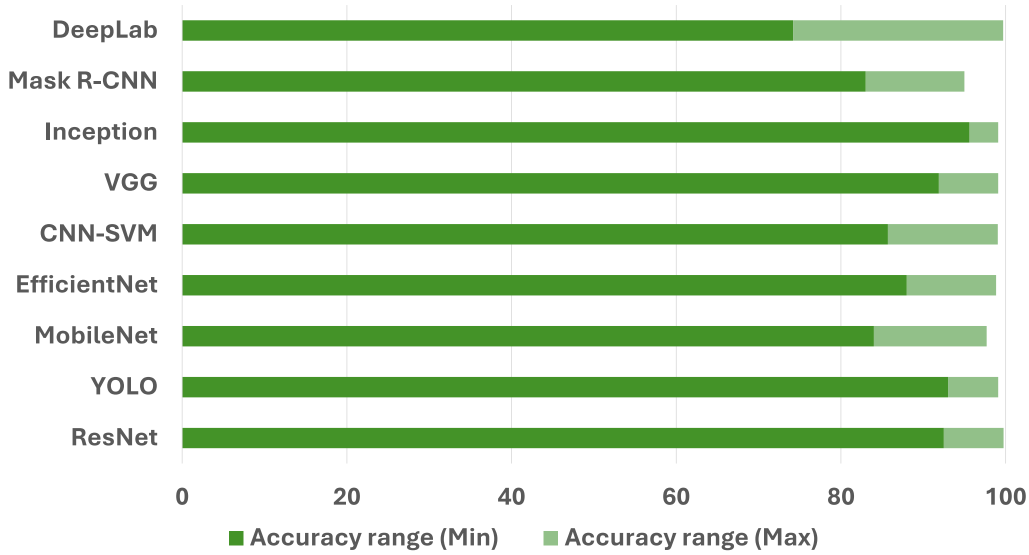

Figure 10. Accuracy ranges of selected models for plant disease detection. The horizontal bars represent the variability in performance across different datasets and experimental setups, as reported in the literature.

The variability in model architecture, datasets, and preprocessing methods made a comprehensive comparative analysis impractical. This review summarizes trends and identifies key gaps, like the need for robust augmentation and real-time detection. It synthesizes trends and suggests areas for future validation, despite limited direct comparisons.

In addition to advances in research in machine learning for plant disease detection, several commercial developments demonstrate the practical application of these technologies. As an example, [203,204] detail methods to improve accuracy in the identification of plant diseases and pests through image analysis and the integration of environmental data. Similarly, [205] highlights the use of active learning to improve model precision while reducing manual data labeling costs. Other patents, such as [206,207], focus on intelligent monitoring systems and lightweight models optimized for mobile devices, enabling real-time field applications. These innovations illustrate the growing potential of machine learning in agriculture, opening up opportunities for more automated and efficient disease management solutions.

5. Conclusions

This systematic review has highlighted significant advances and the effectiveness of machine learning techniques in the detection of pests and diseases in crops. Through a detailed examination of recent studies, it has become evident that CNNs are particularly effective in processing complex image data to identify and classify various plant diseases and pest damage. These technologies not only improve the accuracy of diagnosis but also offer a rapid response capability that is crucial for timely pest management and disease control in agriculture. The integration of machine learning into agricultural practices promises not only to enhance crop productivity but also to contribute toward sustainable farming practices by reducing the reliance on chemical pesticides and improving resource management.

Furthermore, the findings of this review advocate for continued research and development in this field. Future research should focus on several key areas, including enhancing datasets to improve the robustness of models under diverse environmental conditions, developing more sophisticated algorithms that account for variability in crop types and disease manifestations, and advancing the real-time deployment of these models in the field through mobile and edge computing technologies. Additionally, integrating machine learning systems with Internet of Things (IoT) devices for continuous monitoring and early detection, as well as exploring the use of other machine learning paradigms like unsupervised learning and reinforcement learning, offers promising directions for reducing the reliance on manual annotations and improving model generalization.

On a broader scale, interdisciplinary collaboration between machine learning experts, agronomists, and policymakers is essential to ensure that these solutions are scalable, economically viable, and accessible to farmers in both developed and developing regions. Future studies could also investigate ethical implications and concerns about data privacy related to the widespread adoption of these technologies in agriculture to ensure that innovations align with the goals of societal and environmental sustainability.

Finally, although this review has synthesized relevant findings from the Scopus database, there may be valuable research present in other databases that have been overlooked. Future work could broaden the scope to include a wider variety of sources, providing a more complete understanding of progress in this field. Furthermore, research could focus on developing models that are more adaptable and generalizable, reducing the dependency on crop-specific datasets and addressing disease pattern variations due to environmental factors. Evaluating model performance across diverse environmental settings and data types would also provide practical insights, helping to advance the robustness and applicability of these models in real-world agricultural contexts and perform empirical evaluations across standardized benchmarks. Moreover, the variability in reported metrics across studies and proprietary or unpublished methods could also be analyzed, enabling a direct comparison of methodologies across metrics such as accuracy, computational efficiency, and robustness to environmental variability. Such a framework could also facilitate the empirical validation of the trends identified in this review.

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Abbreviations

The following abbreviations are used in this manuscript:

Acronym	Description
1D-ResNet	One-Dimensional Residual Network
3D CNN	Three-Dimensional Convolutional Neural Network
AdaBoostSVM	Adaptive Boosting Support Vector Machine
AISDLT	Artificial Intelligence System using Deep Learning Techniques
ANN	Artificial Neural Network
ANN-HOG	Artificial Neural Network with Histogram of Oriented Gradients
BAT-BCDPBM	Bootstrap Crop Disease Prediction Model with BAT Algorithm
BEiT	Bidirectional Encoder Representations from Transformers
BoVW	Bag of Visual Words
CAE	Convolutional Autoencoder
CapsNet	Gabor Capsule Network
CCA-YOLO	Correlation Coefficient Analysis with You Only Look Once
CenterNet	Center-based Object Detection Network
CNN	Convolutional Neural Network
CNN-HCF	Convolutional Neural Network with Hand-Crafted Features
CNN-LSTM	Convolutional Neural Network with Long Short-Term Memory
CNN-ReLU	Convolutional Neural Network with Rectified Linear Unit
CNN-SVM	Convolutional Neural Network with Support Vector Machine
CoDet	Cotton Detection Network
ConLSTM-U-Net	Convolutional Long Short-Term Memory U-Net
Conv-3 DCNN	3-Layer Convolutional Deep Neural Network
CRUNet	Vanilla Network with Channel Reconstruction Unit
CSA	Crow Search Algorithm
C-SVM	Cost-sensitive Support Vector Machine
DbneAlexNet	Deep Batch Normalized AlexNet
DbneAlexNet	Deep batch normalized AlexNet
DCDM	Deep Convolutional Decision Module
DCGAN	Deep Convolutional generative adversarial network
DCNN	Deep Convolutional Neural Network
dCNN	Lightweight Deep Convolutional Neural Network
DeepLabV3	Deep Learning Lab Version 3
DLMC-Net	Deeper Lightweight Multi-Class Convolutional Neural Network
DLPDS	Deep Learning Plant Disease Detection System
DnCNN	Denoising Convolutional Neural Network
DNN-CSA	Deep Neural Network optimized using Crow Search Algorithm
DT	Decision Trees
DV-PSO-Net	Deep Mutual Learning Model with Particle Swarm Optimization
E-CNN	Enhanced Convolutional Neural Network
EfficientNet	Efficient Neural Network
EfficientNetv2-S	Efficient Neural Network Version 2 Small
EffiNet-TS	Efficient Network Time Series
EKNN	Enhanced K-Nearest Neighbor
FA-SVM	Hybrid Firefly Algorithm with Support Vector Machine
FCDCNN	Edge-Cloud Fuzzy Deep Convolutional Neural Network
Few-shot	Few-shot Learning
GA-Kmeans-ANN	Genetic Algorithm with K-means and Artificial Neural Network
GAN	Generative adversarial network
GLCM	Gray-Level Co-occurrence Matrix
GoogLeNet	Google Network Residual Network
GPR-CNN	Algorithm Particle Swarm Optimization Convolutional Neural Network
GPR-CNN	Genetic Algorithm Particle Swarm Optimization Convolutional Neural Network
HCF	Hand-Crafted Features
HCO-CNN	Hybrid Crow Optimization-based Convolutional Neural Network
HXTL-COKELM	Hybrid Xception Transfer Learning with Crossover Optimized Kernel Extreme Learning Machine
I-LDD	Interpretable Leaf Disease Detector
Inception V3	Inception Version 3
Inception-ResNet	Inception Residual Network
IRNN-TL	Transfer Learning with Improved Recurrent Neural Network
KNN	K-Nearest Neighbors
LC3Net	Lightweight Convolutional Neural Network with Channel Attention and SPPF Module
LDA	Linear Discriminant Analysis
LeIAP	Least Important Attention Pruning
LR	Logistic Regression

LTriTP	Local Triangular-Ternary Pattern
Mask R-CNN	Mask Region-based Convolutional Neural Network
MDSCIRNet	Multi-head Attention Mechanism Depthwise Separable Convolution Inception Reduction Network
ML-HOG	Machine Learning with Histogram of Oriented Gradients
ML-LM	Machine Learning with Extreme Learning Machine
MLR	Modified Logistic Regression
M-Net	Modified AlexNet
MobileNet	Mobile Neural Network
MobileNetV2	Mobile Neural Network Version 2
MobileNetV3	Mobile Neural Network Version 3
MResNet	Modified Residual Network
MSA-CNN	Multi-Scale Selective Attention CNN
MSSOA	Memetic Salp Swarm Optimization Algorithm
Multi-class SVM	Multi-Class Support Vector Machine
NB	Naïve Bayes
NCA	Neighborhood Component Analysis
NN	Neural Network
ODCNN	Optimized Deep Convolutional Neural Network
PDDCNN	Potato leaf disease detection Convolutional Neural Network
PeachNet	Peach Detection Network
PLS-LDA	Partial Least Squares Discriminant Analysis
PMF+FA	Pre-training Meta-learning Fine-tuning with Feature Attention
PWDNet	Pine Wilt Disease Network
R-CNN	Region-based Convolutional Neural Network
RDODL-APDC	Red Deer Optimization with Deep Learning for Agricultural Plant Disease Detection and Classification
RDTNet	Residual Deformable Transformer Network
ResNet	Residual Network
ResNet-101	Residual Network 101 layers
ResNet-50	Residual Network 50 layers
ResNeXt	Residual Network with Next-Generation Features
RF	Random Forest
RFBDB-GAN	Residual Feature Block Dense Block generative adversarial network
RiceNet	Rice Detection Network
RM-SVM	Redundant Multi-Class Support Vector Machine
RSODL-PDDC	Rat Swarm Optimization Deep Learning Plant Disease Detection and Classification
S-CNN	Segmented Convolutional Neural Network
SegNet	Segmentation Network
Sentinel-2	Sentinel Satellite Data 2
SE-VRNet	Support Vector Machine and K-Nearest Neighbors Squeeze-and-Excitation Visual Recognition Network
SLIC	Simple Linear Iterative Clustering
SMbRF	Spider Monkey-based Random Forest
SSAFS	Swarm Algorithm for Feature Selection
SVM	Support Vector Machine
TeenyNet	Teeny Neural Network
T-HOG	Triangular Histogram of Gradient
Unet	Modified U-shaped Convolutional Neural Network
V	Various
VGG16	Visual Geometry Group 16
VirLeafNet	Viral Leaf Detection Network
VOCs	Volatile Organic Compounds
WD2CNN	Wasserstein Distance to Convolutional Neural Network
WeedDet	Weed Detection Network
XGBoost-KNN	XGBoost with K-Nearest Neighbors
YOLOv3	You Only Look Once Version 3
YOLOv4	You Only Look Once Version 4
YOLOv5	You Only Look Once Version 5

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