A Review on

"Plant Leaf Disease Detection and Classification Using AI and Computer Vision Techniques"

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Abstract

Agriculture is a vital industry and a primary source of income for many nations. Diseases in plants caused by pathogens such as viruses, fungi, and bacteria result in significant financial losses globally in the agricultural sector. Monitoring and ensuring the quality and quantity of crops require effective plant disease management. Disease symptoms are often visible on various plant parts, with leaves being the most affected. Researchers have utilized computer vision, deep learning, few-shot learning, and soft computing techniques to automatically identify plant diseases using leaf images. These technologies enable farmers to take timely and accurate actions to prevent declines in crop yield and quality. By automating disease detection, these methods overcome limitations such as subjective feature selection, manual feature extraction, and inefficiencies in traditional approaches, enhancing both research speed and technology effectiveness. Additionally, molecular techniques have been developed to mitigate pathogenic threats. This review examines the use of machine learning, deep learning, and few-shot learning for automated plant disease detection, highlights diagnostic techniques to prevent disease, and explores future directions in disease classification.

Keywords: Deep learning, diagnosis, image processing, machine learning, and plant disease.

Introduction

The United Nations' Food and Agriculture Organization has reported a consistent increase in global hunger since 2015. Current estimates suggest that approximately 680 million people are undernourished, accounting for less than 9% of the global population. This represents an annual increase of 10 million people and a rise of around 120 million over the last decade. Moreover, over 85% of the global population depends on agriculture for sustenance, underscoring the critical need for efficient farming mechanisms. Plants also play a vital role in maintaining environmental balance by producing oxygen through photosynthesis. However, plant diseases, particularly those affecting leaves, can severely impact plant health and disrupt food production. A historical example is the 1845 Irish Potato Famine, which caused 1.2 million deaths due to crop failure [1]. Laboratory techniques such as immunosorbent enzyme assays, isothermal amplification, and polymerase chain reaction (PCR) are commonly employed to detect plant diseases.

Early detection, effective management, and prevention of plant diseases are essential. However, diagnosing diseases in large agricultural fields is challenging, requiring skilled personnel and visual inspection of plant leaves [2]. Farmers typically rely on their experience to identify symptoms, a process that is time-intensive, laborious, and demands specialized skills. Automated disease detection systems aim to assist non-experts, including non-pathologists and non-botanists.

This review explores automated techniques utilizing image processing, machine learning, deep learning, and few-shot learning for plant disease detection. Traditional machine learning approaches often lack robustness and are confined to controlled laboratory settings [3]. In contrast, deep learning has recently demonstrated remarkable success in classifying plant disease images. However, deep learning methods require extensive datasets, with images meticulously annotated by pathologists and botanists. These processes are resource-intensive and costly. Few-shot learning (FSL) offers an alternative by enabling models to learn from limited labeled datasets [4], where the number of samples depends on the experiment's objectives and complexity.

Various pathogens contribute to plant diseases and can be identified using molecular techniques such as DNA analysis, PCR, MPG (Modified Panchayat Mixture), ELISA (Enzyme-Linked Immunosorbent Assay), FISH (Fluorescence in Situ Hybridization), and IF (Immunofluorescence) methods. This review paper provides a comparative analysis of machine learning, deep learning, and few-shot learning in plant disease detection. It also examines segmentation, feature extraction, and classification techniques alongside molecular diagnostic tools [5].

Objective

The objective of the project "Plant Leaf Disease Detection and Classification Using AI and Computer Vision Techniques" is to develop an intelligent system capable of identifying and classifying plant leaf diseases accurately and efficiently. By leveraging advanced AI algorithms and computer vision, the system aims to assist farmers and agricultural professionals in detecting diseases at an early stage, reducing crop losses and improving productivity. The solution seeks to be user-friendly, cost-effective, and scalable, enabling real-time monitoring of plant health through a mobile or web interface. Ultimately, this project aims to support sustainable farming practices by minimizing the overuse of pesticides and promoting precision agriculture.

Phytopathology

Phytopathology refers to the study of plant pathogens, the diseases they cause, their mechanisms, and methods to control and mitigate their impact on plants. It serves as a comprehensive framework for understanding and managing a plant's life cycle. Derived from Greek, "Phytopathology" combines "Phyto" (plant), "Patho" (disease), and "Logo" (knowledge) [6]. Its core objectives include investigating the origins and causes of plant diseases, whether biotic or abiotic (etiology), understanding the mechanisms behind disease development (pathogenesis), examining interactions between plant pathogens and diseases (epidemiology), and developing strategies to reduce damage and manage losses, as depicted in Fig. 1.

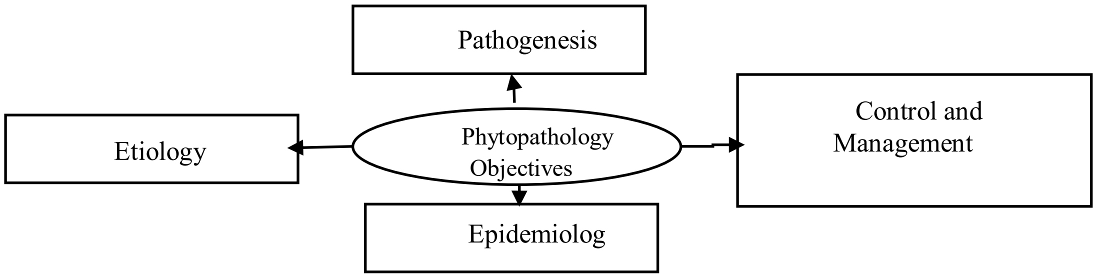

Fig 1. Phytopathology objectives.

Phytopathology is a specialized subfield within agricultural science that integrates foundational knowledge from diverse disciplines such as microbiology, physiology, nematology, virology, anatomy, bacteriology, mycology, genetic engineering, botany, meteorology, climatology, and molecular biology, as illustrated in Fig. 2.

Plant disease: types and symptoms

Abnormalities in the behavior or physiology of plants lead to diseases, which can be caused by biotic or abiotic agents, as shown in Fig.2 [16]. Biotic diseases result from infectious agents, while abiotic diseases are caused by non-infectious factors. Abiotic diseases are generally less hazardous and non-transmissible, making them easier to prevent. This manuscript focuses on biotic diseases.

Fig 2. Subdomains of phytopathology

- <u>Bacterial Diseases</u>: Bacterial infections in plants typically begin as water-soaked lesions that develop into small green blemishes. Over time, these lesions expand and dry into dead spots, as illustrated in Fig. 4. For instance, foliage may display water-soaked black blemishes, brown leaf spots, or yellow halos of uniform size. Under dry conditions, the blemishes often appear dappled. Bacterial wilt, a common issue in brinjal crops, causes the entire plant to collapse [7].
- <u>Viral Diseases</u>: Viral infections in plants are among the most challenging to diagnose, as they may exhibit no visible symptoms or mimic signs of herbicide damage or nutrient deficiencies [7]. Commonly observed viral diseases include those transmitted by beetles, leafhoppers, aphids, and whiteflies, such as mosaic viruses, which manifest as green or yellow streaks on foliage, as shown in Fig. 4.
- <u>Fungal Diseases</u>: Fungal infections affect various parts of plants, including stems, leaves, seeds, and roots. Examples include sclerotium wilt, stem rust, blight, ergot, and carnal bunt. Late blight caused by *Phytophthora* fungus initially appears as gray-green waterlogged blemishes on older leaves, as shown in Fig. 3. Over time, these lesions darken, and white fungal growth may appear due to fluctuating wet and dry conditions [8]. Early blight caused by *Alternaria* fungus produces small brown blemishes with a characteristic concentric ring pattern, as shown in Fig. 3. Rust fungi form spots on mature leaves that turn black over time, as illustrated in Fig. 4.

The described symptoms are distinct but limited compared to the wide range of plant diseases. Similar symptoms may arise from both infectious and non-infectious causes, as summarized in Table 1.

Table 1 Distinct disease in different plants.

Author	Plant Name	Bacterial Disease	Viral Disease	Fungal Disease
Kianat et al. 2021 [9] Agarwal et al. 2021 [10]	Cucumber	Brown Blemnish, Angular Blemnish, Target Blemnish	Mosaic, Yellow Blemnish	Black Blemish, Gray Mold
Shrivastava et al. 2019 [11] Chen et al. 2021 [12]	Rice	Streak, Blight	Black Dwarfed Streaked	Smut False
Sun et al. 2021 [13]	Maize	Streak, Stalk	Crimson, Dwarf	Rust
Abbas et al. 2021 [14]	Tomato	Canker	Curl leaf yellow	Late/Early Blight

Accurate diagnosis of plant diseases is a challenging task, as it requires distinguishing between pathogens based on specific symptoms. The effectiveness of artificial intelligence (AI) techniques in disease detection largely depends on feature extraction and classification [15]. These extracted features help identify disease symptoms and improve classification accuracy. Table 2 highlights examples of typical plant diseases and their associated symptoms, aiding researchers in selecting accurate features for high-performance disease detection.

Table 2. Distinct plants, their disease and responsible pathogen

Plants	Diseases	Pathogens	Symptoms
Apple	Scab	PomiSpilocal	Brown-Gray on leaf
	Rot	MalorumSphaeropsis	Dark Brown on leaf
	Rust	Sporangium	Yellow pale on leaf
Cherry	Mildew	Clandestina	Gray powder on leaf
Corn	Gray Spot	Cercospora	Rectangle lesions
	Rust	Sorghipuccinia	Red pustules on leaf
	Light blight	Tutcicasetosphaeria	Elliptical lesions
Grape	Rot	Bidwelliiguignardia	Red borders on leaf
	Measles	Aleophilum	Necrotic stripping
	Isariopsis blight	Angulata brachypus	Coalesce lesions
Peach	Spot	Arboricola Xanthomonas	Clustered lesions
Potato	Early blight	Solani Alternaria	Brown lesion
	Late blight	Infestans phytophthora	Dark greeb spot
Tomato	Septoria spot	Lycopersici	Foliage
	Mosaic	Mosaic virus	Mottle green leaf
Orange	Green Citrus	Bacteria Motile	Precipitate Demolition
Strawberry	Scorch Fungus	Diplocarpon	Brown edges
Squash	Mildew	Xanthiipodosphaers	White powder

Fig3 (a) Bacterial blemish (b) Viral Mosaic (c) Late Blight (d) Early Blight (e) Rust.

Plant disease detection system

Artificial intelligence (AI) techniques play a crucial role in enhancing agricultural productivity by enabling effective plant disease monitoring. Numerous studies have been conducted in this area [16], with some focusing on specific methods and others on individual diseases. However, a comprehensive review of plant disease detection, classification, and diagnostic techniques remains unavailable.

This review aims to bridge that gap by exploring various approaches employed by researchers, including machine learning (ML), deep learning (DL), few-shot learning (FSL), and soft computing techniques integrated with image processing for analyzing RGB and hyperspectral images. Additionally, molecular techniques are discussed, which have been developed to prevent and mitigate pathogenic threats effectively.

MACHINE LEARNING:

The process of detecting plant diseases using machine learning and image processing follows a series of sequential steps: Image Acquisition**,** Image Preprocessing**,** Image Segmentation**,**

Feature Extraction and Selection**,** and Classification [17]. These steps are detailed below, along with key approaches proposed in the literature.

1) Image Acquisition:
   This is the initial step in any machine learning system, involving capturing images or retrieving them from repositories. The quality of these images significantly impacts the system's disease detection accuracy, [18]. Captured images may contain undesirable elements like background noise or shadows, which need to be removed for better analysis. In addition to standard RGB images, specialized cameras are used to capture hyperspectral, thermal, and fluorescent images. Consequently, the performance of the system relies heavily on the quality of images obtained during this stage. Table 3 summarizes datasets used in plant disease detection.

Table 3. Details of the dataset available used by various researchers.

	Dataset Name	Authors
Open accessible dataset	APS Image dataset	Arnab Barbedo et. al. 2019 [18]
	Plant village image dataset	
	Computers & optics in food inspection (Cofi) laboratory image dataset	Bashir et. al. 2019 [19]
	Digipathos Images (PDDB)	
	IRRI dataset	
	INIBAP Leaf dataset	
Self-created dataset	RoCoLe	Parraga Alava et. al. 2019 [20]
Multiple crop dataset	Citrus Dataset	Masazhar& Kamal et. al. 2018 [21]
	Grape Fruit Grove	

2) Image Preprocessing: Image preprocessing is crucial to enhance image quality by eliminating distortions, turbulence, or shadows, especially in datasets captured in uncontrolled environments [22]. This step improves system accuracy and reduces processing time through operations such as cropping, resizing, and background removal. Common preprocessing techniques include image enhancement, noise removal, and augmentation methods like noise injection, flipping, gamma correction, scaling, rotation, shifting, zooming, and brightness/contrast adjustments.

Table 4. Details of techniques used by various researchers.

	Technique Used	Authors
Color Space Conversion	Enhancement	Kaur et al. 2018 [22],
	Filtering,	
	Background reduction RGB, HSV, HSI, YIQ, L*a*b, grayscale	
Image Enhancement Technique	Denoising Using mean and median filtering	Goncharov et. al. 2019 [23]
	Illumination variation using histogram equalisation	
Thresholding techniques	Adaptative Thresholding, Entropy, classification of diseases and pests	M. Francisco et al. 2023 [24]
Clustering	k-means	Kaur et al. 2018b [22],
		Bashir et al. 2019 [19]
Feature Descriptor	GLCM, Wavelet Transform, Haralick feature, Gabor Transform, Local Binary Patterns, SURF	Bhagat & Kumar 2023 [25]
Texture Feature	GLCM Features	Deshapande et al. 2019 [26],

Color feature	Color co-occurrence matrix	Chouhan et al. 2019 [27]
Feature Descriptor	discrete wavelet transforms and SVM	S. M. Kiran et al. 2021 [28]

3) Image Segmentation: Image segmentation isolates the region of interest (e.g., infected areas) from the rest of the image. This step simplifies analysis by clearly separating affected and unaffected areas. Segmentation methods are broadly categorized into:
   - Conventional Techniques: Thresholding, region growing, and edge detection.
   - Computational Techniques: Fuzzy logic, genetic algorithms, and neural networks.

Computational methods generally outperform conventional ones. The segmentation process is essential for accurate feature extraction. Table 5 highlights segmentation techniques used by researchers.

4) Feature Extraction: Feature extraction is essential for distinguishing different parts of an image. Extracted features, such as color, texture, and shape, are critical for disease classification. The accuracy of plant disease detection systems heavily depends on effective feature extraction techniques [27]. To prevent overfitting and reduce computational costs, feature selection methods are employed to identify the most relevant features. Techniques like Principal Component Analysis (PCA), genetic algorithms, and particle swarm optimization are commonly used. Table 6 provides a summary of feature extraction techniques, while Fig. 4 illustrates trends in feature extraction research over the past 12 years.

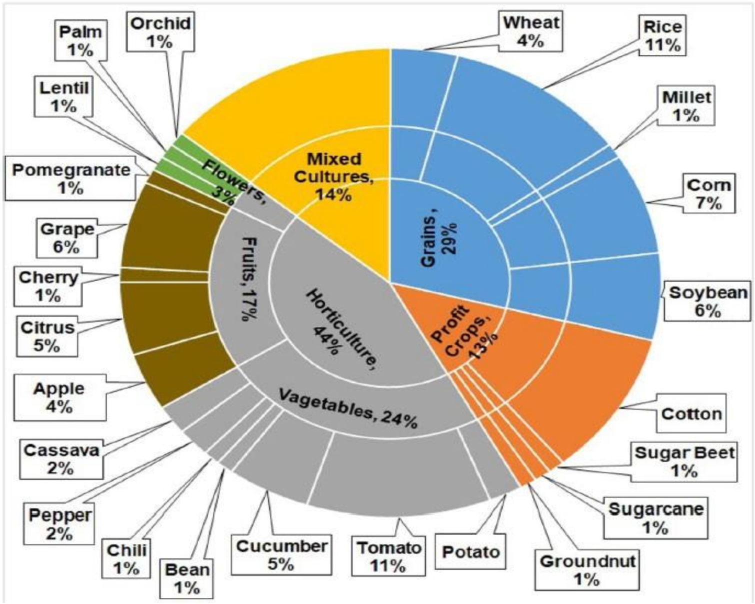

Fig 4. Different feature extraction techniques for distinct crops during last 12 years

5) Classification: Classification is the final and most critical stage in machine learning systems. The effectiveness of this step depends on the preceding stages (acquisition, preprocessing, and feature extraction/selection). In plant disease detection, this step involves training a dataset to classify test images as healthy or defective based on disease symptoms. Machine learning (ML) techniques are broadly categorized as:
   Supervised Learning: Uses labeled data for training.
   - Unsupervised Learning: Uses unlabeled data for training.
   - Semi-Supervised Learning: Combines labeled and unlabelled data.

Additionally, vegetation index and fuzzy logic-based techniques are occasionally employed. Table 5 provides a comparative analysis of their performance in plant disease detection systems.

Table 5 Details of classification technique used by various researchers

	Authors	Dataset	Feature Extraction	Classifier	Accuracy (%)
Rice	Joshi & Jadhav 2017 [28]	Agriculture Research(115)	Color & Shape	MD & k-NN	88.15
	Zhang et al. 2018a [29]				
	Bashir et al. 2019 [19]	60	Haar & SIFT	Vegetation Index	
	Shrivastava & Pradhan 2021 [31]			SVM	63
	Rath & Meher 2019 [32]	-	Color		
				SVM	94.16
		APS (440)	SIFT		
					94.65
		Real FieldImages	-	Radíal Basis NN	
		Real Field Images			95.00
			-		

Wheat & Corn	Azadbakht et al. 2019 [33]	Academy(744)	Index based	Regression	95.00
	Kusumo et al. 2019 [34]	Hyperspectral data			
	Deshapande et al. 2019 [26]	Plant Village(3823)	SIFT, SURF	SVM, DT, RF, NaïveBayes	87.00
		Agriculture University Dharwad (200)	First Order histogram & GLCM	k-NN, SVM	88.00
Soyabean	Pires et al. 2016 [38]	Federal (1200)	SIFT, SURF, HOG	SVM	96.25
	Kaur et al. 2018b [19]				
		Plant Village (4775)	Color, Texture, Shape	SVM	84.00
Millet	Caulibaly et al.2019 [35]	Self (124)	Transfer Learning	VGG16	89.00
Sugar beet	Hallau et al. 2017 [36]	Self (1400)	Texture	SVM	82.00
Cane	Pujari et al. 2016 [37]	Self (9912)	RGB Color	SVM & EBPNN	92.00
Mix	Sladojevic et al. 2016 [39]	Internet (33469)	-	CNN	95.80
	Ferentinos 2018 [25]	Plant Village & Self (87848)	TransferLearning	Alexnet, VGG	99.53
Apple	Jolly & Ramam 2016 [40]	Self (320)	Haarlick& LBP	SVM	96.00
Citrus	Sharif et al. 2018 [41]	Image Gallery dataset	Color, Texture, Geometrical	Multiclass SVM	95.80
Cherry	Sengar et. al. 2018 [42]	Plant Village	Lesion Area	-	99.00
Grape	Javidam et al. 2023 [43]	Self	GLCM	Inception V3	98.97
				SVM	
Cucumber	Zhang et al. 2017 [44]	Self	PHOG	SVM	91.48
Tomato	Bhatia et al. 2021 [45]	Mildew	-	SVM Log Reg	92.73

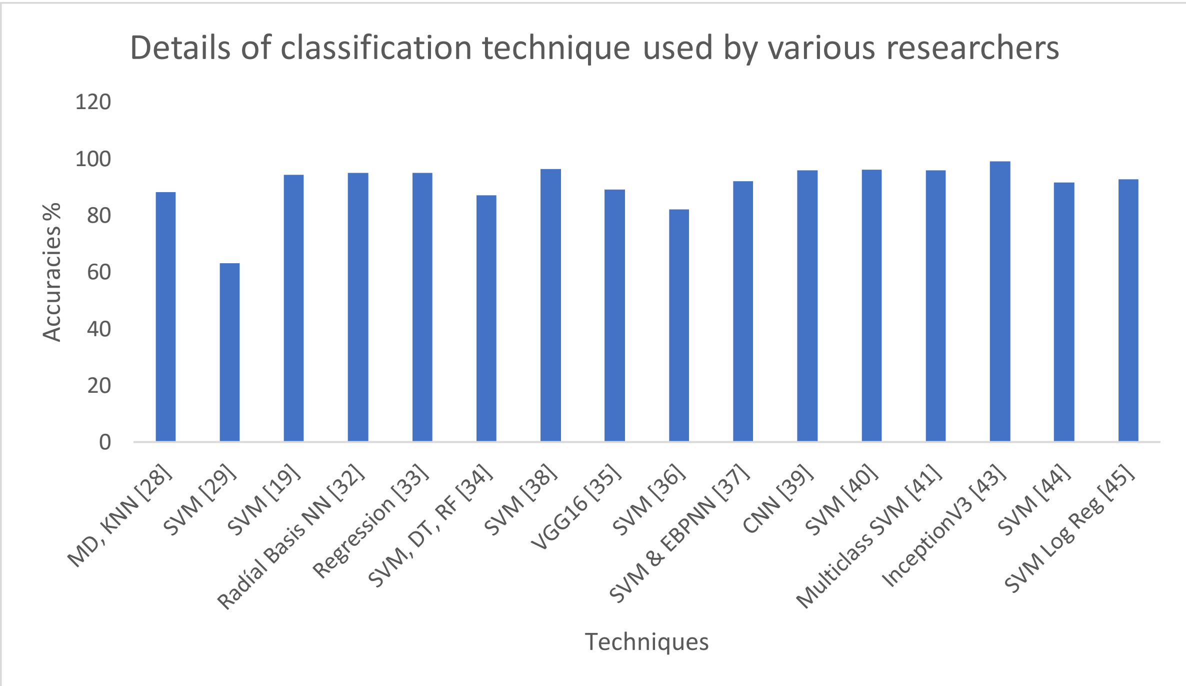

Fig. 5 Chart showing classification technique used by various researchers

DEEP LEARNING USING IMAGE PROCESSING:

Deep learning (DL), introduced in 1943, is a hierarchical approach to machine learning, enabling object detection [46], image classification, and natural language processing. It builds high-level features by combining low-level ones, enhancing generalization and accuracy compared to traditional machine learning techniques. The development of DL has progressed through three phases:

- Phase 1 (1943–1969): Linear neural network models for classification.
- Phase 2 (1986–1988): Non-linear mapping using multilayer perceptron and the backpropagation (BP) algorithm.
- Phase 3 (2006–Present): Introduction of ReLU activation functions, ImageNet recognition, and advanced models like AlexNet.

Modern DL techniques automatically select features, forming high-level representations by combining lower-level ones. Advanced neural networks include convolutional neural networks (CNNs), multilayer perceptrons, and recurrent neural networks. Prominent CNN architectures such as Alex-Net, Google-Net, VGG-Net, Mobile-Net, Res-Net, and Efficient-Net have been developed over time.

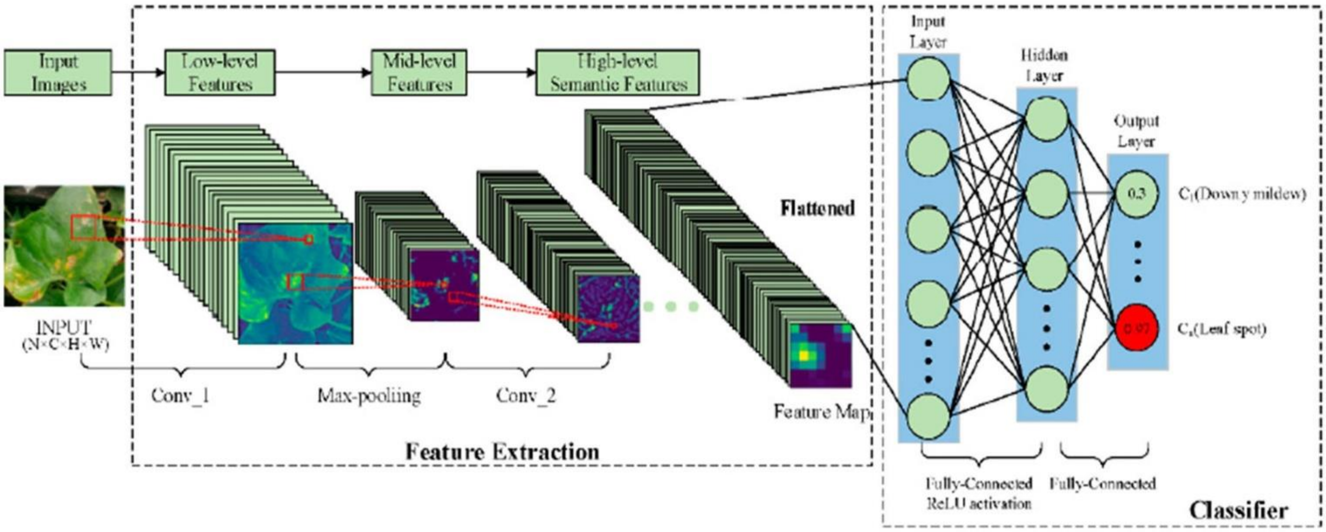

Fig 6. Essential steps for implementing Deep Learning

The essential steps for implementing DL, particularly CNNs, involve the following stages as shown in Fig 5:

1. Image Acquisition: High-quality data acquisition is critical for developing accurate models. DL datasets are typically divided into three sets:
    - Training Set: Used for model learning.
    - Validation Set: Adjusts hyperparameters.
    - Test Set: Evaluates performance.

    Publicly available datasets like PlantVillage and Kaggle [47] are commonly used in plant disease classification studies, as shown in Table 8. Additional datasets can be sourced from platforms like BIFROST (accessed November 15, 2023) and Kaggle (accessed November 12, 2023). Some researchers also

    Table 8. Bulky publicly available dataset used in

2. Image Augmentation: Deep learning requires large datasets, but collecting sufficient data can be resource-intensive, particularly for plants with short growth cycles. Data augmentation addresses this challenge by expanding datasets without altering the fundamental features (e.g., color) crucial for disease detection. Conventional augmentation techniques include:
    - Rotation
    - Saturation adjustment
    - Mirroring (symmetry)

    Advanced augmentation methods like AugMix, Fast AutoAugment, CutMix, population-based augmentation, and RandAugment improve dataset diversity and quality. However, conventional augmentation techniques sometimes suffer from limited diversity and inconsistency. Researchers have used these methods to enhance system efficiency, as outlined in Table 6.
3. Image Classification: DL has demonstrated significant success in classifying plant diseases, but challenges remain in terms of transparency and interpretability. These systems are often described as "black boxes," lacking detailed explanations of their decision-making processes.

Table 6. Details of data augmentation technique is used by various researchers

Author	Datasets	Techniques	Accuracy increased (%)
Bin et al. 2017 [48]	1053 – 13689	PCA	4.00
Srdjan et al. 2016 [49]	4483 – 33469	Rotation	3.00
Nazki et al. 2020 [50]	2789	ARGAN	5.20
Tain et al. 2019 [51]	TeaImage	CycleGAN	28.00
Wu et. al. 2020 [52]	GoogleNet	DCGAN	94.33
Liu et. al. 2020 [53]	Grape	LeafGAN	94.02
Lin et al. 2019 [54]	10820 – 32460	Radial Blur	3.15
Arnal Barbedo 2019 [55]	1567 – 46409	Segmentation	12.00

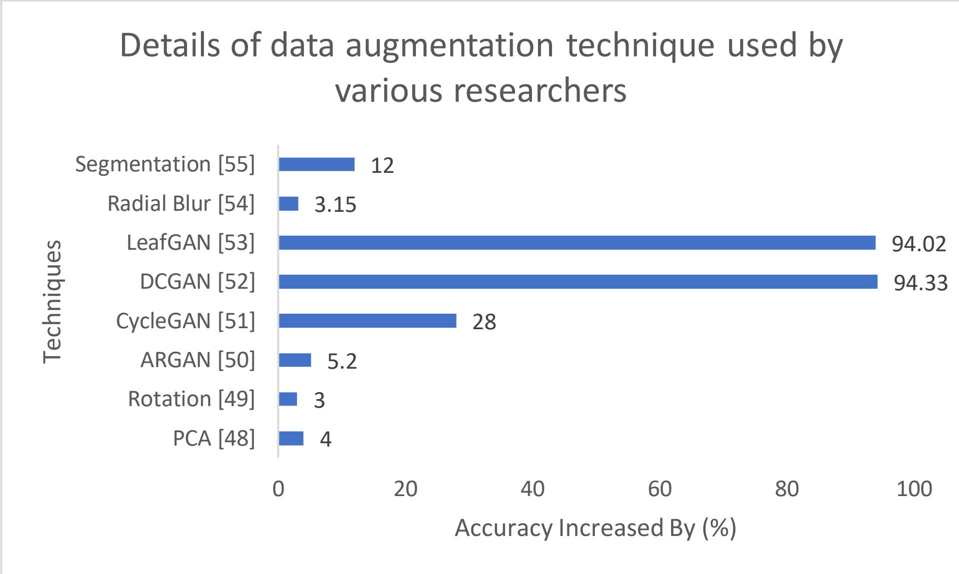

Fig. 7 Chart showing percentage increase by various techniques

HYPERSPECTRAL IMAGING WITH IMAGE PROCESSING:

Plant diseases are sometimes challenging to detect through computer vision systems or visual inspection due to the growth stages of pathogens. Hyperspectral imaging sensors, operating primarily within the electromagnetic spectrum range of infrared and visible light (400–2500 nm), capture detailed information across a wide range of bands. This sensitivity to leaf variations caused by different diseases enables early detection of plant pathologies. Hyperspectral imaging has proven effective for early-stage plant disease detection. Wang et al. (2019) [56] proposed a GAN-based model called OR-AC-GAN (Outlier Removal—Auxiliary Classifier GAN) for detecting tomato leaf diseases, achieving 96.25% accuracy. Advances in sensor technology for pathogen detection, summarized in Figure 6 and Figure 7, highlight the application of these sensors in agricultural disease management, enabling scalable observation and management.

- Imaging Technologies in Plant Disease Detection: RGB Imaging: RGB sensors capture basic digital images for disease detection and identification. Improvements in technical parameters such as light sensitivity, optical focus, and spatial resolution have significantly enhanced their effectiveness.
- Multispectral and Hyperspectral Sensors: Multispectral sensors assess spectral information across several wavebands, including RGB and near-infrared. Hyperspectral sensors, on the other hand, provide both spatial and spectral data, with resolution depending on the sensor and the target object [57].
- Thermal Sensors: Infrared thermography (IRT) measures plant temperature, correlating it with water status and microclimate. IRT applications span various scales, from small-scale to broader agricultural uses.
- Fluorescence Sensors: These sensors use laser light or LED sources to measure chlorophyll fluorescence, aiding in photosynthetic activity analysis. Combined with image analysis, they help quantify and discriminate fungal diseases.

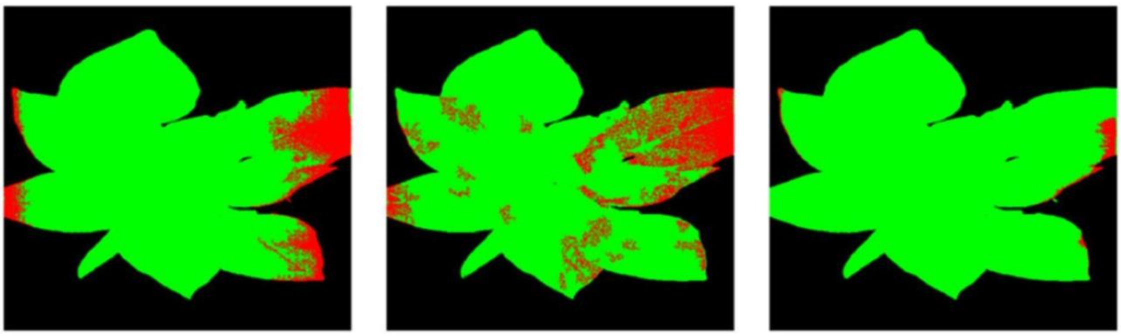

Fig 8. Segmentation comparison(a) DirectCNN (b)AC-GAN (c)OR-AC-GAN

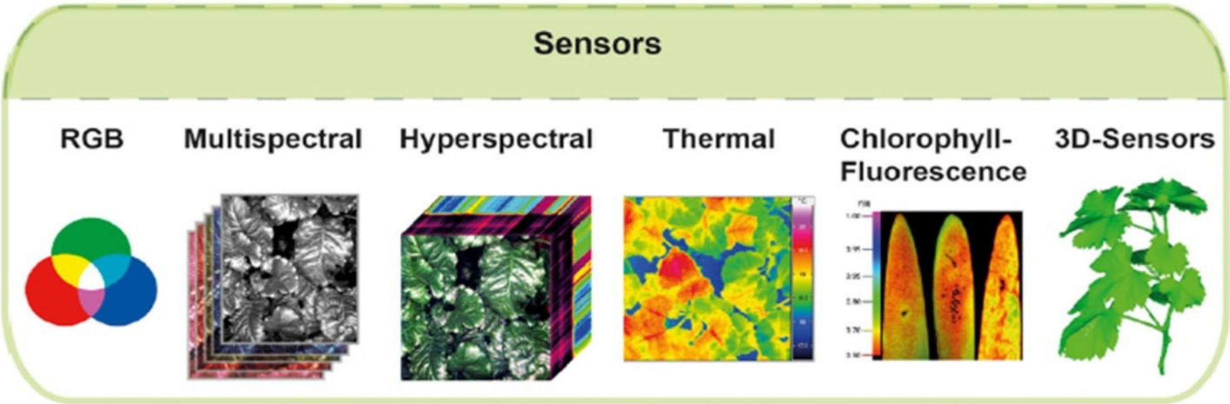

Fig 9. Overview of sensor technologies

FEW-SHOT LEARNING (FSL) WITH IMAGE PROCESSING:

Few-shot learning (FSL) is a machine learning paradigm that enables models to learn from limited labeled datasets. The complexity of the problem and the objective of the experiment influence the number of "shots" required. FSL leverages prior knowledge and datasets during training, optimizing data and models to generate source tasks. FSL is particularly suitable for plant disease detection where datasets are limited in size. Table 13 illustrates various FSL-based techniques for small-sample plant disease detection. Key FSL Techniques:

- Embedding: This involves feature extraction or dimensionality reduction techniques. Pre-trained CNNs (e.g., ImageNet) reduce training time, while SVM with distinct kernels classifies complex systems.
- Multitask Learning: A shared model trains multiple tasks using either hard parameter sharing (HPS) or soft parameter sharing (SPS). In HPS, common parameters are shared across tasks, while SPS trains specific features for individual tasks.
- Transfer Learning: This approach reuses existing knowledge to reduce training time and enhance model performance.
- Meta-Learning: Also known as "learning to learn," meta-learning optimizes model performance by leveraging experiences from multiple tasks, improving generalization to new datasets.

Transfer learning is considered the most robust among these techniques. However, FSL methods are computationally intensive relative to performance gains. Future work focuses on enhancing FSL algorithms to improve plant disease recognition and conduct comprehensive performance evaluations of different FSL methods.

MOLECULAR DIAGNOSIS TECHNIQUES:

Pests and diseases can cause up to 35% losses in global food production. Early detection is crucial to prevent outbreaks of severe plant diseases caused by pathogens such as nematodes, viruses, bacteria, fungi, and oomycetes. Molecular diagnostic techniques bridge the gap between traditional methods and the need for precise disease management. Below are key molecular technologies:

- ELISA (Enzyme-Linked Immunosorbent Assay): Widely used in plant pathology, ELISA detects specific substances in samples via antibody-enzyme interactions, leading to a color change. However, it has limitations in sensitivity and specificity, especially for bacterial pathogens.
- Conventional PCR: This molecular biology technique amplifies DNA sequences using electrophoresis for pathogen detection. While sensitive, it is susceptible to contamination and false positives.
- Real-Time PCR (RT-PCR): A quantitative PCR method offering high sensitivity and specificity for detecting DNA pathogens. It minimizes cross-contamination risks and is particularly effective for known gene sequences.
- LAMP (Loop-Mediated Isothermal Amplification): A cost-effective, rapid alternative to RT-PCR. It uses specific DNA primers under isothermal conditions, allowing for efficient amplification and detection with minimal equipment.
- Biosensors: These devices integrate biochemical reactions with transducers for detecting various chemical compounds. They offer cost-effective, sensitive, and simple diagnostic solutions across fields like agriculture, medicine, and food safety.
- Next-Generation Sequencing (NGS): NGS is a high-throughput sequencing technology capable of processing large DNA sequences efficiently. It has revolutionized molecular diagnostics, enabling applications such as metagenomics and single-cell sequencing. However, its use in diagnosing plant pathogens remains limited to specific cases.

Limitations

Automated plant disease detection has made significant progress; however, several limitations persist at various stages of the process. One primary challenge is the difficulty in obtaining samples for specific diseases. The type of dataset used—whether laboratory-controlled or real-time—greatly impacts system performance. Data from uncontrolled environments increases system complexity but is highly relevant for agricultural advancements and modern research. Common classification techniques for plant disease detection include SVM, ANN, Naïve Bayes, backpropagation neural networks, decision trees, and k-nearest neighbors, [30][31]. Convolutional Neural Networks (CNNs) have shown superior performance on large datasets, but overfitting remains a significant issue in deep learning-based systems for plant disease detection. Efforts to enhance the efficiency of CNN-based systems for multi-crop disease detection have been reported in the literature. To address these challenges, proposed systems must meet essential specifications. Overlooking any specification can lead to inaccurate disease detection. Therefore, researchers should design versatile systems with adjustable parameters rather than rigid specifications. Overfitting continues to hinder the practical application of machine learning in this domain, emphasizing the need for highly generalized and adaptable systems. While machine learning remains a powerful tool due to its diverse techniques and resources, maintaining accuracy must remain a priority.

Challenges

The literature highlights several challenges in plant disease detection, one of which is the lack of expert annotators capable of accurately differentiating between dead plants and those infected by disease. This task demands skilled professionals, which can be costly and particularly challenging for rare or newly emerging diseases. Additionally, employing deep learning (DL) techniques for modeling, hyperparameter tuning, and training requires substantial resources, posing another significant hurdle. While shallow architectures perform well with smaller datasets, recent advanced models provide new perspectives for building effective plant disease detection systems. Incorporating machine learning (ML), deep learning (DL), and few-shot learning (FSL) is recommended to enhance these models. Future research should focus on improving plant disease detection, classification, and quantification to advance smart agriculture. Key challenges and factors affecting plant disease classification and identification include:

- Feature Extraction and Classification: System performance heavily depends on the techniques used for feature extraction and classification.
- Dataset Dependence: Many studies rely on the Plant Village dataset, which consists of laboratory images, rather than real-time images, significantly impacting classifier performance.
- Complex Backgrounds: Real-world images often have complex backgrounds, making it difficult to segment affected areas, which hampers system performance.
- Nutrient Deficiency and Contamination: Early-stage nutrient deficiencies and contamination can complicate disease detection.
- Pesticide Management: Estimating infected areas and managing disease severity can help optimize pesticide use.
- Real-Time Efficiency: Designing systems that operate efficiently on constrained devices remains a challenge.
- Hyperparameter Tuning: Proper tuning and selection of hyper parameters can significantly impact system performance.
- Uniformity and Attribute Selection: Disease identification systems face difficulties due to the uniformity of certain diseases and challenges in attribute selection.

Tentative Solutions

Addressing the challenges in plant disease detection requires innovative and multidisciplinary approaches. For feature extraction and classification, leveraging transfer learning with pre-trained models can significantly reduce the need for extensive manual feature engineering. Additionally, advanced techniques like genetic algorithms or principal component analysis (PCA) can optimize feature selection, enhancing system performance. To mitigate dataset dependence, researchers should prioritize creating diverse datasets using real-world images collected from various agricultural environments. Data augmentation and synthetic image generation can further simulate real-world variations, while crowd-sourced data collection from farmers can enrich dataset diversity.

The complexity of real-world backgrounds presents another significant obstacle, but robust segmentation algorithms, such as U-Net or Mask R-CNN, can effectively isolate plant regions from complex scenes. Domain adaptation methods can further improve model robustness to background intricacies. For distinguishing nutrient deficiencies and contamination from diseases, integrating multi-sensor data, such as hyperspectral imaging and thermal sensors, offers promising results. Analyzing time-series data can also provide insights into the progression of plant health issues.

Optimizing pesticide management can be achieved by incorporating spatial analysis and disease severity quantification into detection systems. These advancements can inform decision support systems that combine detection outputs with agronomic data to guide effective pesticide application. Ensuring real-time efficiency remains a critical challenge, especially for deployment on resource-constrained devices. Lightweight models such as MobileNet or EfficientNet, coupled with techniques like model pruning and quantization, can address this issue.

Hyperparameter tuning, a key determinant of model performance, can be streamlined using automated approaches such as Bayesian optimization, grid search, or random search. Cloud-based platforms can also provide scalable solutions for computationally intensive tuning processes. Finally, the uniformity of certain diseases and challenges in attribute selection can be addressed using few-shot learning, enabling models to generalize effectively with limited data. Ensemble methods that combine predictions from multiple models focusing on distinct disease attributes can further improve classification accuracy. These solutions collectively pave the way for advancing plant disease detection, classification, and management in the era of smart agriculture.

Conclusion

The emergence of plant pathogens poses a significant threat to global food security, ecosystems, and economies. Factors such as globalization, increased mobility, vectors, climate change, and pathogen evolution have accelerated the spread of invasive plant pathogens. To address agricultural losses, the development of automated approaches for plant disease detection and classification is urgently needed. This review explores the use of machine learning (ML), deep learning (DL), and few-shot learning (FSL) for automated plant disease recognition. It highlights key methodologies, including acquisition, preprocessing, segmentation, feature extraction, and classification. While many studies rely on RGB images, some have adopted hyperspectral imaging for plant leaves, which offers the advantage of detecting microscopic symptoms without requiring labeled datasets. These automated techniques have facilitated timely advancements in research. Additionally, the review examines molecular diagnostic tools and state-of-the-art techniques for plant disease detection. The methods discussed are highly sensitive, specific, and capable of rapid detection. Future research should focus on integrating server-side systems with mobile applications and leveraging electrophysiology to enhance plant disease detection. Such innovations hold great potential for advancing agricultural disease management and offer valuable guidance for future studies.

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