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Smart Detection Techniques for Plant Leaf Diseases Using Deep Learning : A Systematic Literature Review

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Abstract

Agriculture is an essential part of ensuring global food security, but crop productivity is frequently threatened by plant diseases. Leaf diseases on tomato crops, in particular, can cause substantial losses if not identified early. Traditional disease identification methods rely on visual inspection, which is labor-intensive and prone to error. In recent years, deep learning techniques, especially convolutional neural networks (CNNs), have gained attention for automated plant disease diagnosis using leaf images. This paper presents a comprehensive review of existing deep learning approaches for tomato leaf disease detection, focusing on CNN architectures, attention mechanisms such as squeeze-and-excitation (SE) blocks, data augmentation strategies, and training optimizations. The reviewed studies are categorized according to network architecture, dataset, plant species, and reported performance metrics. Publicly available datasets, such as PlantVillage, are discussed, along with limitations in real-world applicability due to domain shift. Challenges faced by existing methods, including dataset bias, class imbalance, and overfitting, are highlighted. Finally, research gaps are identified, and directions are suggested to enhance the robustness, generalization, and practical applicability of deep learning-based plant disease diagnosis systems for sustainable agriculture.

Keywords: Tomato Leaf Disease; Deep Learning; Convolutional Neural Networks; Survey; Image-based Classification.

1 | Introduction

Tomato (Solanum lycopersicum) is one of the most economically and nutritionally valuable horticultural crops worldwide. In Egypt, tomato farming contributes significantly to the agricultural industry, ranking fourth globally in production. In the 2022–2023 cycle, Egypt produced 7.1 million tons, representing an 11.7% increase from the previous year [1]. Despite this growth, tomato crops are highly susceptible to foliar diseases, including early blight, late blight, and leaf mold. Early blight, caused by Alternaria solani, can lead to severe defoliation, fruit sunburn, and substantial yield losses [2,3]. Effective monitoring and early detection are essential to mitigate these losses. Traditional visual inspection methods are time-consuming, subjective, and challenging to scale in industrial or resource-limited agricultural settings [4,5]. In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have been widely adopted for automated plant disease detection using leaf images [6–8].

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These methods can extract meaningful features automatically, without manual feature engineering. However, deploying such models in real-field conditions remains challenging due to hardware limitations and trade-offs between model size and predictive accuracy [9–11]. While several surveys have reviewed deep learning approaches for plant disease detection, most either focus on general agricultural AI, individual model families, or laboratory datasets. Few studies systematically analyze recent advancements specifically for tomato leaf diseases, compare model architectures, attention mechanisms, data augmentation strategies, and real-world deployment challenges, or identify critical research gaps. Therefore, a focused and up-to-date survey is necessary to consolidate knowledge, highlight limitations in existing methods, and guide future research toward more robust, generalizable, and field-applicable plant disease detection systems.

This paper provides a review of deep learning-based approaches for tomato leaf disease detection, covering CNN architectures, attention mechanisms (e.g., squeeze-and-excitation blocks), data augmentation strategies, and training optimizations. The reviewed studies are analyzed with respect to network design, datasets, target plant species, and reported performance metrics.

The paper is organized as follows. Section 2 presents the review methodology, including the literature search strategy, selection criteria, and PRISMA-based screening process. Section 3 discusses the importance of early detection in plant disease management. Section 4 provides a comparative review of existing deep learning–based approaches for plant leaf disease detection. Section 5 highlights the key challenges and limitations associated with developing efficient and deployable detection systems. Finally, Section 6 concludes the review and outlines potential directions for future research.

To help readers quickly grasp the overall workflow and methodological landscape

of deep learning–based plant leaf disease detection systems, Figure 1 presents a high-level graphical overview of the complete pipeline, from data acquisition and preparation to classification and evaluation.

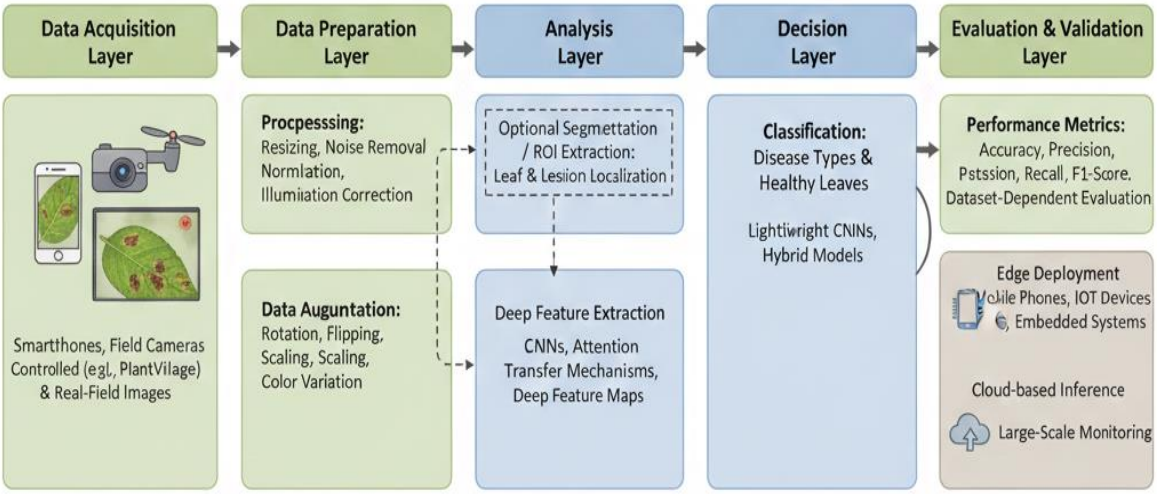

Figure 1. High-level graphical summary of deep learning approaches for plant leaf disease detection.

2 | Review Methodology

This review follows a structured and systematic methodology to ensure transparency, reproducibility, and comprehensive coverage of recent deep learning–based approaches for plant leaf disease detection. The review process adheres to the general principles of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework.

2.1 | Search Strategy

A comprehensive literature search was conducted to identify relevant studies published between 2020 and 2025, reflecting recent advances in deep learning architectures and deployment-oriented plant disease detection systems. The search focused on peer-reviewed journal articles and high-quality conference proceedings.

The primary sources of literature included widely used scientific databases and publishers, such as IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, MDPI, and related indexed venues. Search queries were formulated using combinations of keywords including:

plant disease detection, leaf disease classification, deep learning, convolutional neural networks, lightweight CNN, transfer learning, hybrid models, edge deployment, and PlantVillage dataset.

In addition to benchmark datasets such as PlantVillage, studies employing custom and field-collected datasets were explicitly considered to capture real-world variability and deployment-oriented research trends.

2.2 | Search Strategy

To ensure relevance and consistency, explicit inclusion and exclusion criteria were applied during the screening process. Inclusion criteria:

- Studies published between 2020 and 2025.
- Research articles proposing or evaluating deep learning–based models for plant leaf disease detection.
- Studies using image-based datasets, including PlantVillage or custom/field datasets.
- Articles reporting quantitative performance metrics (e.g., accuracy, precision, recall, F1-score).
- Works describing model architecture, computational complexity, or deployment considerations.

Exclusion criteria:

- Studies published before 2020.
- Review papers, surveys, or opinion articles without experimental validation.
- Works not based on deep learning or not using image-based plant disease data.
- Papers with insufficient methodological detail or unavailable full text.
- Duplicate studies or extended versions of the same work with overlapping results.

2.3 | Study Selection Process (PRISMA Flow)

The study selection process followed a structured multi-stage screening procedure inspired by the PRISMA framework, as illustrated in Figure 2 (The study selection process). Initially, 112 records were identified through comprehensive searches across multiple digital libraries, including IEEE Xplore, SpringerLink, ScienceDirect, Google Scholar, in addition to reference list screening.

After removing 18 duplicate records, 72 unique studies remained and were screened based on titles and abstracts. During this stage, 28 records were excluded due to irrelevance to plant leaf disease detection, absence of deep learning methodologies, or insufficient experimental validation.

Subsequently, 66 full-text articles were assessed for eligibility. Of these, 16 studies were judged ineligible because they were published before 2020, lacked experimental evaluation, or did not focus on image-based leaf disease detection.

Finally, 56 primary studies were selected for qualitative synthesis and comparative analysis. These studies constitute the analytical foundation of the review and are systematically categorized in Tables 1–3, reflecting diverse architectural designs, dataset characteristics, and deployment considerations.

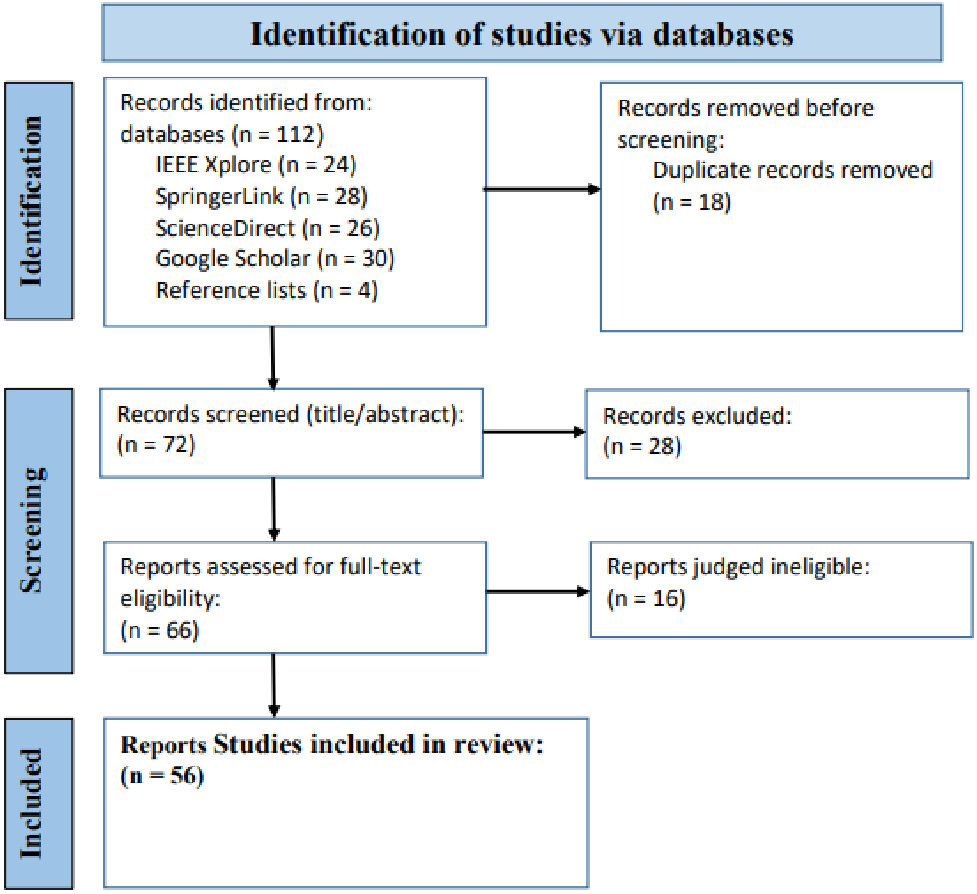

Figure 2. The study selection process.

2.4 | Data Extraction and Categorization

For each selected study, relevant information was systematically extracted, including:

- Model architecture and design strategy,
- Target plant species,
- Dataset type and size (PlantVillage or custom datasets),
- Reported performance metrics,
- Model size and computational complexity,
- Suitability for edge or resource-constrained deployment.

To enable structured comparison and deeper insight, the selected studies were categorized into three groups, each comprising a representative set of works:

1. Pre-trained and transfer learning–based models (Table 1),
2. Enhanced and customized CNN architectures (Table 2),
3. Hybrid and cascaded deep learning models (Table 3).

Each group includes approximately ten representative studies, selected to balance architectural diversity, dataset variation, and reported performance. This grouping strategy facilitates meaningful qualitative comparison while avoiding bias toward a single architectural family or dataset.

2.5 | PRISMA Summary

In summary, the review methodology ensures that:

- The literature selection process is systematic and reproducible,
- Recent and experimentally validated studies are emphasized,
- Comparisons are made on a qualitative and architectural basis, rather than relying solely on reported accuracy values,
- Practical considerations such as deployability and computational efficiency are explicitly addressed.

3 | The importance of Early Detection in Agricultural Disease Management

Early detection of crop diseases is crucial for reducing yield losses, maintaining product quality, and sustaining agricultural productivity. Foliar diseases, such as early blight in tomatoes and potatoes, typically begin with subtle signs, including small lesions, browning, or mild leaf deformation. If not detected early, these infections can spread rapidly, causing significant economic losses [1, 2].

Early identification of diseases, including viral infections like Tomato Yellow Leaf Curl Virus (TYLCV), enables timely interventions such as targeted pesticide application or removal of infected plants, preventing large-scale outbreaks and minimizing environmental impact [5]. Conventional visual inspection methods are labor-intensive, time-consuming, and prone to human error, especially under variable field conditions. In contrast, computer-based and deep learning approaches have shown significant potential for early detection using image analysis [9, 10]. These techniques can detect subtle changes in leaf color and texture before they become visible to the naked eye, enabling pre-symptomatic identification. Integration with mobile or drone platforms further enhances field monitoring and decision-making.

Other technologies, such as template matching for pathogen detection and multispectral imaging for crop disease monitoring, illustrate the trend toward scalable and field-deployable solutions [3, 4]. By reducing reliance on laboratory testing and facilitating timely interventions, early detection supports sustainable agriculture, precision farming, and smart farming initiatives, ultimately contributing to improved food security for both large-scale and smallholder farms.

4 | Comparative Study

This section reviews recent AI-based approaches for plant disease detection, with a focus on deep learning techniques, datasets, and imaging methods. Advances in data availability, image processing, and AI algorithms have facilitated faster and more accurate detection of plant diseases. Farmers and researchers are increasingly applying AI to monitor crops, support decision-making, and improve agricultural productivity [12].

Smart farming, integrating AI and IoT, enables precise monitoring and management across different crop growth stages. Plant disease detection primarily relies on leaf images captured by cameras, drones, or satellites. Several datasets are available for research, among which the PlantVillage Dataset is most commonly used [13]. It contains 54,306 images of plant leaves under controlled conditions, covering 38 classes across 14 plant species, including Tomato, Cherry, Squash, Apple, Orange, Potato, Strawberry, Raspberry, Grape, Blueberry, Bell Pepper, Soybean, and Peach. These classes include 12 healthy, 17 fungal, 4 bacterial, 2 viral, 2 mold-related, and 1 mite-related diseases. While these datasets are diverse, they are largely lab-controlled, which may limit applicability to field conditions and real-world deployment.

The following subsections discuss various AI-based methods applied to plant disease detection, highlighting their network architectures, data augmentation strategies, attention mechanisms, and reported performance metrics.

This paper presents a critical and systematic survey of deep learning techniques for plant leaf disease detection, focusing on convolutional neural networks (CNNs) and related architectures. The primary research objective is to provide a comprehensive overview of the current state-of-the-art methods, highlighting their architectural designs, data requirements, performance metrics, and practical deployment considerations.

Rather than proposing a new model, this survey aims to answer the following research question: What are the main challenges, limitations, and effective strategies in applying deep learning models for accurate and efficient detection of plant diseases under diverse real-world conditions? By addressing this question, the paper identifies gaps in the literature and informs future research directions for improving robustness, generalization, and efficiency in AI-based plant disease detection systems.

4.1 | Deep Learning Techniques for Plant Leaf Diseases Detection

Deep learning (DL) techniques have been extensively applied to automate plant leaf disease detection, providing a significant improvement over traditional manual inspection, which is labor-intensive and prone to human error [14]. Convolutional Neural Networks (CNNs) and their variants constitute the predominant DL approach for image-based classification tasks in this domain, owing to their ability to automatically extract hierarchical features from input images [15], [16]. Among publicly available datasets, PlantVillage remains the most widely utilized, comprising over 54,000 labeled images spanning 14 plant species and multiple disease categories, including tomato leaf diseases [13]. However, the dataset was primarily collected under controlled laboratory conditions, which may not fully capture the variability present in real-field environments. Factors such as illumination changes, background complexity, and crop variability introduce a domain shift, potentially leading to degraded performance when models trained on controlled datasets are deployed in real-world agricultural settings.

To ensure a systematic and reproducible survey, the studies reviewed herein were identified through structured searches in major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search encompassed publications from 2015 to 2024, using keywords such as “tomato leaf disease detection,” “plant disease deep learning,” “CNN,” and “attention mechanisms.” Inclusion criteria were applied to select studies that: (i) focused on DL approaches for plant leaf disease detection, (ii) reported performance metrics on publicly available or well-documented datasets, and (iii) provided sufficient methodological details to enable comparative assessment. Studies lacking quantitative results, not relevant to plant disease detection, or restricted to non-public datasets were excluded. This protocol ensures transparency in study selection and supports reproducibility of the comparative survey presented in subsequent sections.

Challenges in applying DL models to plant disease detection include dataset imbalance, variations in lighting conditions, hardware constraints, and the need for models that generalize effectively across diverse environments. To address these challenges, researchers have developed a range of models, from lightweight CNNs suitable for mobile or edge deployment to deeper hybrid architectures targeting higher accuracy. In addition to CNNs, other DL algorithms employed include recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and multilayer perceptrons (MLPs), with CNNs being the most extensively utilized [15], [16]. Several well-established CNN architectures have been adapted for plant disease detection, including AlexNet [17], Xception [18], Inception [19], VGG [20], and ResNet [21]. These models leverage hierarchical feature extraction to identify complex patterns associated with different disease symptoms. The studies selected for this review focus specifically on tomato leaf disease detection and the use of publicly available datasets, providing a solid foundation for comparative evaluation of architectures, data augmentation strategies, and reported performance metrics. Figure 3 provides hierarchical taxonomy of deep learning models for plant leaf disease detection, illustrating the relationships between standard CNN architectures, pre-trained networks, enhanced or customized models, and cascaded or hybrid frameworks.

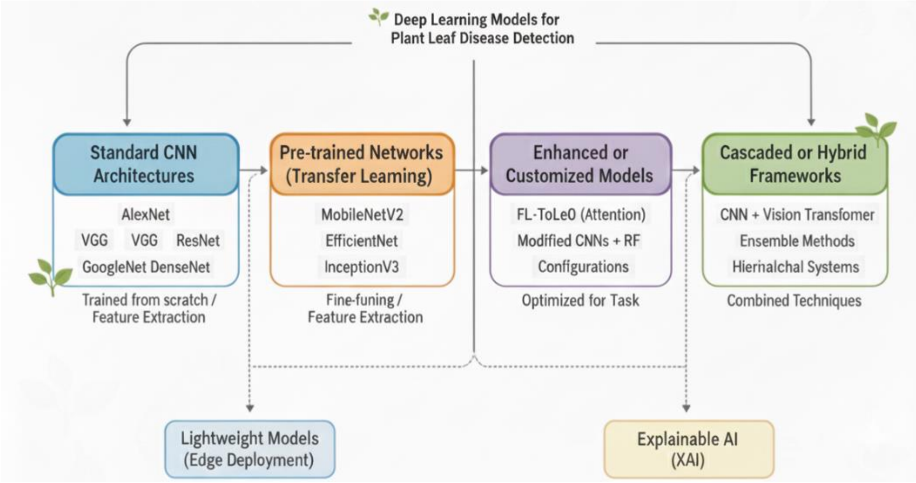

Figure 3. Hierarchical taxonomy of deep learning models for plant leaf disease detection.

4.2 | Pre-Trained Models for Plant Leaf Diseases Detection

Transfer learning has become a widely adopted approach in plant disease detection, enabling researchers to leverage pre-trained convolutional neural network (CNN) architectures such as AlexNet, MobileNet, DenseNet, VGG, ResNet, and EfficientNet. These models are initially trained on large-scale benchmark datasets (e.g., ImageNet) and subsequently fine-tuned for domain-specific tasks, including plant leaf disease classification [22–31].

Recent studies have explored various strategies to enhance model performance. For example, DenseNet121 was combined with synthetic image generation techniques to improve generalization and reduce overfitting [22]. MobileNetV2 integrated with runtime data augmentation was applied to improve robustness against dataset variability [24]. Other architectures such as ResNet50 [25], VGG16 [26], and InceptionV3 [27] were explored across different crop species, demonstrating the adaptability of pre-trained networks for diverse plant disease detection tasks.

Lightweight and efficiency-oriented models, including EfficientNet variants [28,29] and SqueezeNet [30], have been proposed to address deployment constraints in resource-limited agricultural environments.

To provide a structured overview, Table 1 presents a qualitative summary of ten representative pre-trained deep learning models for plant leaf disease detection, focusing on studies published between 2020 and 2025. The studies included were selected based on multiple criteria:

1. Relevance to tomato leaf disease detection, while including other crops to illustrate the cross-species applicability of pre-trained CNNs.
2. Diversity of CNN architectures, including both lightweight models suitable for edge deployment (MobileNet, SqueezeNet) and deeper networks with strong feature extraction capabilities (VGG16, ResNet50, DenseNet121, EfficientNetB5).
3. Publication recency and impact, prioritizing studies from 2020–2025 with notable methodological contributions and practical relevance.
4. Practical deployment considerations, such as model size, computational cost, and suitability for low-resource devices.

This curated selection provides readers with a concise yet informative overview of pre-trained CNN models, emphasizing both performance and practical deployment considerations. Limiting the table to ten studies maintains clarity while capturing the most relevant examples.

Accuracy values in Table 1 are extracted from the original studies and presented as reported, typically to two decimal places. "Ref. No." indicates the reference number of the cited study; "Plant" specifies the host plant; "Dataset Size" is the number of images used for training and testing; "Accuracy (%)" represents the classification accuracy; "Model Size" is reported in number of parameters; "Edge Deployable" indicates whether the model can be deployed on resource-constrained devices; "Advantages" summarizes key strengths; "Disadvantages" summarizes main limitations.

From Table 1, several general observations can be drawn:

- Lightweight architectures such as MobileNetV2 and SqueezeNet are more suitable for real-time deployment on edge devices, whereas larger models like VGG16 and ResNet50 achieve high accuracy but are computationally intensive.
- Model performance generally improves with dataset size and the use of appropriate data augmentation, but larger models do not always guarantee better deployability in low-resource environments.
- Hybrid or enhanced models (e.g., DenseNet121 with synthetic image augmentation or EfficientNetB5) show improved generalization and robustness, illustrating the trade-off between complexity and practical deployment.
- Overall, this table emphasizes practical advantages, limitations, and deployability considerations rather than providing a strict quantitative ranking, helping readers identify suitable architectures for specific field applications.

Table 1. Qualitative summary of pre-trained deep learning models for plant leaf disease detection.

Ref. No.	Model Architecture	Plant	Dataset Size	Accuracy (%)	Model Size	Edge Deployable	Advantages	Disadvantages
[22]	DenseNet121	Tomato	PlantVillage (16,012)	97.11	8 Million Parameters	NO	Uses synthetic data (C-GAN) for better generalization	Slightly below top-performing models
[23]	AlexNet	Tomato	PlantVillage (3,000)	98.49	61 Million Parameters	NO	Preprocessing and feature enhancement improve classification	Large model, not ideal for low-end devices
[24]	MobileNetV2	Tomato	PlantVillage (18,160)	99.30	3.4 Million Parameters	YES	Compact, runtime augmentation improves robustness	Overfitting and negative transfer risks
[25]	ResNet50	Apple	PlantVillage (12,000)	97.20	25.6 Million Parameters	NO	Strong performance on complex inputs	High computational cost
[26]	VGG16	Tomato	PlantVillage (5,000)	94.80	138 Million Parameters	NO	Reliable and widely used	Very large model, not suitable for embedded devices
[27]	InceptionV3	Grapevine	PlantVillage (8,000)	98.50	23.8 Million Parameters	NO	Excellent accuracy and balanced metrics	Computationally demanding
[28]	CNN (Custom)	Multi-crop	PlantVillage (~8,000)	96.10	Not Reported	NO	Simple CNN architecture with competitive accuracy	Limited scalability and edge deployment details
[29]	EfficientNetB5	Tomato	PlantVillage (11,000)	99.07	30 Million Parameters	YES	Efficient and accurate	High complexity, not real-time friendly
[30]	SqueezeNet	Banana	PlantVillage (937)	96.25	1.2 Million Parameters	YES	Extremely lightweight, fast inference	Limited generalization
[31]	EfficientNetB7	Grape	PlantVillage (9,027)	98.70	66 Million Parameters	NO	High precision, compact	Very low recall, possible class imbalance

4.3 | Enhanced and Altered Models for Plant Leaf Diseases Detection

Beyond standard transfer learning approaches, several studies have proposed customized or enhanced convolutional neural network (CNN) architectures to improve plant leaf disease detection. These models are primarily designed to overcome limitations observed in conventional CNNs, such as class imbalance, limited generalization on small datasets, high computational cost, and restricted deployability on mobile or edge devices.

Beyond transfer learning with pre-trained architectures, a second category of studies focuses on enhanced and customized CNN models specifically designed or modified for plant leaf disease detection. These approaches aim to reduce architectural complexity, improve feature localization, and address limitations such as overfitting, class imbalance, and real-time deployability—particularly in agricultural environments with limited computational resources. The ten studies summarized in Table 2 [32–42] were selected based on three main criteria:

i. the use of customized or structurally modified CNN architectures rather than direct fine-tuning of standard pre-trained models;

ii. publication within the 2021–2023 period, reflecting recent methodological trends; and

iii. explicit reporting of architectural enhancements, dataset characteristics, or efficiency-related considerations relevant to practical deployment.

This selection enables a focused and fair comparison within a homogeneous methodological group, avoiding direct comparison with large-scale pre-trained networks discussed in Table 1.

Early customized CNNs trained on relatively small, crop-specific datasets demonstrated high precision, recall, and F1-scores despite modest overall accuracy, revealing both the sensitivity of such models to dataset size and their susceptibility to overfitting [32,35]. In contrast, lightweight CNN architectures evaluated on larger benchmark datasets—such as PlantVillage—achieved a more balanced trade-off between accuracy and computational efficiency, making them more suitable for mobile and edge-based agricultural applications [33].

Several studies introduced architectural enhancements to improve feature representation and disease localization. Attention mechanisms were incorporated to emphasize disease-affected regions, leading to notable gains in classification accuracy, albeit with increased parameter counts and computational overhead [34]. Other works explored modified loss functions to address class imbalance and multi-crop classification scenarios, resulting in improved F1-scores but sometimes reduced generalization to unseen data [35].

Additional strategies, including image enhancement, feature fusion, ensemble learning, and hybrid CNN frameworks, were proposed to improve robustness across varying crop types and disease patterns [36–40].

From a deployment perspective, a clear trade-off emerges between model accuracy and efficiency. Extremely lightweight architectures, such as convolutional autoencoder–CNN hybrids with only a few thousand parameters, demonstrate strong potential for edge deployment but may be more sensitive to noise and real-field variations [41]. Conversely, highly complex multi-channel CNNs inspired by Inception-based designs achieve state-of-the-art accuracy across multiple crops but impose significant computational and memory demands, limiting their suitability for real-time or low-resource agricultural settings [42].

Table 2 provides a qualitative comparison of these enhanced and customized CNN-based approaches, emphasizing architectural modifications, dataset scale, reported accuracy, model size, and practical deployability. Rather than presenting a strict quantitative ranking, the table facilitates aggregated insight into the trade-offs between performance, robustness, and computational efficiency.

Overall trends observed from Table 2 indicate that:

- Lightweight and compact CNN architectures achieve competitive performance while offering greater suitability for edge and mobile deployment.

- Attention-based and feature-enhanced models improve localization and classification accuracy but increase architectural complexity.
- High reported accuracy does not necessarily translate into practical deployability, particularly for real-time field applications.
- Models evaluated on small or single-crop datasets often report optimistic metrics that may not generalize well to real-world agricultural conditions.

Consequently, enhanced and customized CNN architectures highlight the ongoing trade-off between accuracy, robustness, and deployability, reinforcing the need for balanced model design tailored to realistic agricultural environments.

Table 2. Qualitative summary of enhanced and customized deep learning models for plant leaf disease detection.

Ref No.	Model Architecture	Plant	Dataset Size	Accuracy (%)	Model Size	Edge Deployable	Advantages	Disadvantages
[32]	Basic CNN	Tomato	BananaLSD dataset (3,000)	88.17	Not reported (Lightweight CNN)	YES	High precision, recall and F1 (99%) on small dataset	Low overall accuracy; possible overfitting
[33]	Lightweight CNN	Tomato	PlantVillage (18,160)	96.87	0.494 Million Parameters	YES	Efficient with low parameters (0.494M); suitable for large datasets	Slightly lower accuracy than advanced models
[34]	CNN with Attention	Tomato	PlantVillage (3,000)	98.49	1.42 Million Parameters	can be deployed on edge devices with additional optimization technique	Attention mechanism enhances focus on diseased regions; competitive accuracy	Increased complexity (1.42M parameters); less suitable for low-end devices
[35]	CNN + Modified Loss Function	Tomato	PlantVillage (3,000)	88.17	Not reported (Lightweight CNN)	can be deployed on edge devices with additional optimization technique	High F1-score (99%) due to tailored loss function	Low overall accuracy; limited generalization
[36]	Deep CNN with Image Enhancement	Tomato	PlantVillage (12,693)	97.36	9.5 Million Parameters	NO	High accuracy due to input image enhancement	Large model (9.5M parameters); higher storage requirements
[37]	CNN with Transfer Learning (e.g., VGG)	Apple	PlantVillage (5,000)	95.50	0.15 Million Parameters	YES	Good generalization; compact model (150K parameters)	Limited flexibility outside pretrained domain
[38]	Ensemble CNN	Potato	PlantVillage (6,000)	94.80	High (multiple CNNs)	NO	Ensemble improves robustness and reliability	Higher computational load and inference time
[39]	CNN + Data Augmentation	Strawberry	PlantVillage (4,500)	96.00	Not reported (Moderate size)	can be deployed on edge devices with additional	Improved performance on imbalanced datasets via augmentation	Dependent on quality of augmentation; moderate complexity

						optimization technique		
[40]	CNN with Feature Fusion	Mango	MangoLeaf BD (7,000)	97.50	Not reported (Multi-branch CNN)	can be deployed on edge devices with additional optimization technique	Multi-scale feature fusion enhances representation of disease patterns	Increased training time and memory usage
[41]	Convolutional Autoencoder	Peach	Peach disease dataset (4,457)	98.38	~9 K parameter s	YES	Very lightweight (9K parameters); efficient encoding	May underperform on unseen noise or real-world variations
[42]	Modified MCNN based on InceptionV3	Various crops	–	99.48	Very Large (Inception -based)	NO	State-of-the-art accuracy; strong generalization across crops	High computational complexity; heavy resource usage

4.4 | Cascaded and Hybrid Models for Plant Leaf Diseases Detection

To address limitations observed in single-model CNN architectures, several studies have explored hybrid and cascaded deep learning frameworks that integrate multiple learning components, such as CNNs with RNNs, LSTMs, U-Nets, autoencoders, classical machine learning classifiers, or graph-based models. These architectures aim to enhance feature representation, improve robustness, and capture complementary spatial, temporal, or relational characteristics in plant leaf disease images.

In addition to standalone CNN architectures and customized lightweight models, a third research direction explores cascaded and hybrid deep learning frameworks for plant leaf disease detection. These approaches integrate CNNs with complementary components—such as recurrent neural networks (RNNs), segmentation networks, classical machine learning classifiers, or graph-based models—to enhance feature representation, localization, and classification robustness across diverse crops and datasets.

The ten studies summarized in Table 3 [43–55][43–55][43–55] were deliberately selected based on four criteria:

i). the adoption of multi-stage or hybrid architectures combining CNNs with additional learning or processing modules;

ii). publication within the 2020–2025 timeframe, reflecting contemporary hybrid modeling trends;

iii). coverage of diverse crop species and dataset types, including benchmark and field-collected data; and

iv). explicit discussion of accuracy–complexity–deployability trade-offs.

This grouping enables a focused evaluation of cascaded and hybrid designs as a distinct methodological class, rather than direct comparison with pure CNN or transfer learning approaches presented in Tables 1 and 2.

From an architectural perspective, hybrid models can be broadly categorized into four groups. The first group comprises CNN–sequence-based hybrids, such as CNN–RNN, CNN–LSTM, and CNN–BiLSTM models, which aim to capture dependencies within extracted feature sequences and have shown improved representation capability in tomato and banana disease detection tasks [43,51,53].

The second group includes CNN–segmentation-based pipelines, where CNN classifiers are combined with U-Net or region-of-interest (ROI) extraction modules to improve spatial localization of disease symptoms, particularly for rice and guava datasets [47,48].

The third category consists of CNN–classical classifier hybrids, integrating deep feature extraction with SVM, Random Forest, or KNN classifiers to enhance decision boundaries and interpretability across multiple crops [45,49,50,52].

Finally, recent studies have explored graph-based extensions, such as CNNs coupled with graph convolutional networks (GCNs), to explicitly model relationships among image regions or features, demonstrating strong performance on potato disease datasets [54].

Despite their strong reported accuracy, most cascaded and hybrid architectures introduce additional computational overhead due to multi-stage processing, sequential components, or complex architectural coupling. Consequently, many models—particularly those based on VGG16, ResNet101, or DenseNet backbones—exhibit limited suitability for real-time or edge deployment despite their high classification performance[45,48,51,52].

In contrast, lightweight cascaded solutions leveraging depthwise separable convolutions, attention mechanisms, or texture descriptors such as Local Binary Patterns (LBP) attempt to balance accuracy and efficiency, making them more suitable for deployment on low-end or edge devices [44,55]. However, these models may remain sensitive to noise, background clutter, or complex real-field conditions.

Importantly, reported accuracy values across hybrid and cascaded models should be interpreted with caution. Substantial variations in dataset size, crop species, image resolution, preprocessing pipelines, and evaluation protocols significantly limit the validity of direct quantitative comparison. Therefore, meaningful insight is better obtained by jointly considering accuracy, architectural complexity, model size, and deployability constraints, rather than relying on accuracy alone.

Table 3 provides a qualitative and comparative overview of representative cascaded and hybrid deep learning approaches for plant leaf disease detection, emphasizing the trade-offs between performance, architectural complexity, and practical deployment considerations, rather than serving as a strict quantitative ranking.

Overall observations from Table 3 indicate that:

- Hybrid CNN–sequence models enhance feature modeling but incur higher memory usage and inference latency.
- CNN–segmentation pipelines improve disease localization but often require large computational resources.
- CNN–classical classifier hybrids offer improved decision-making but suffer from slow inference during testing.
- Lightweight cascaded architectures with attention or texture-based features provide a better balance between accuracy and edge deployability.
- High reported accuracy does not necessarily imply real-world suitability, particularly in resource-constrained agricultural environments.

Accordingly, cascaded and hybrid deep learning models highlight the inherent trade-off between performance enhancement and system complexity, underscoring the need for careful architectural selection when targeting real-time and edge-based plant disease detection systems.

Table 3. Qualitative summary of cascaded and hybrid deep learning models for plant leaf disease detection.

Ref No.	Model Architecture	Plant	Dataset Size	Accuracy (%)	Model Size	Edge Deployable	Advantages	Disadvantages
[43]	Hybrid CNN–RNN (ToLeD)	Tomato	PlantVillage	97.20	~5–7 Million	No	Combines spatial and temporal features, improving	Increased latency and training time due to

			(~8,000 images)		parameters		representation capability	sequential RNN component
[44]	CNN with Depthwise Separable Convolution and Soft Attention (FL-ToLeD)	Tomato	PlantVillage (25,127 images)	99.04	~2.1 Million parameters	Yes	Lightweight design optimized for low-end and edge devices with attention-driven focus	Architectural complexity may increase training instability
[45]	VGG16 with SVM classifier	Multiple crops (14 species)	PlantVillage (~54,000 images)	97.82	~138 Million parameters	No	Strong deep feature extraction with robust classical classification	Extremely large model size; unsuitable for embedded or edge systems
[46]	MobiRes-Net (ResNet + MobileNet hybrid)	Olive	Custom field dataset (5,400 images)	97.08	~6–8 Million parameters	can be deployed on edge devices with additional optimization technique	Balanced trade-off between accuracy and efficiency	Moderate memory usage and inference cost
[47]	MobileNetV2 with U-Net segmentation	Guava	Custom dataset (1,316 images)	83.40	~7.5 Million parameters	can be deployed on edge devices with additional optimization technique	Effective disease localization through segmentation	Low classification accuracy on small datasets
[48]	DenseNet with Improved U-Net and ROI Extraction	Rice	Custom dataset (2,988 images)	96.00	~18.5 Million parameters	No	Precise localization of diseased regions and strong detection performance	High computational complexity and memory requirements
[49]	CNN with Random Forest classifier	Apple	PlantVillage (5,000 images)	94.50	~4–6 Million parameters + RF	No	Combines deep feature extraction with interpretable ensemble decision-making	Slow inference due to Random Forest component
[50]	CNN with KNN-based classifier	Rice	Custom dataset (8,500 images)	97.20	~3–5 Million parameters + KNN	No	High accuracy for well-separated classes	Very slow testing due to distance-based KNN computation
[51]	VGG16 with LSTM	Tomato	PlantVillage (6,000 images)	96.90	Over 140 Million parameters	No	Captures sequential patterns in extracted features	Very high memory usage and inference latency
[52]	ResNet101 with SVM	Grapevine	PlantVillage (10,000 images)	98.20	~44 Million parameters	No	Strong deep feature representation and stable classification	Heavy storage requirements and slower runtime
[53]	DenseNet with BiLSTM	Banana	Custom dataset (4,500 images)	95.70	~9–11 Million parameters	can be deployed on edge devices with additional optimization technique	Integrates spatial and temporal feature modeling	Higher training complexity due to BiLSTM
[54]	EfficientNet with Graph Convolutional	Potato	Custom dataset	97.60	~6–8 Million	can be deployed on edge devices	Captures relational information via	Complex implementation and

	Network (GCN)		(3,000 images)		paramet ers	with additional optimizatio n technique	graph-based modeling	increased computational demand
[55]	Deep CNN with Local Binary Patterns (LBP)	Multiple species	PlantVilla ge (18,160 images)	96.50	~2–3 Million paramet ers	Yes	Lightweight architecture with effective texture-based features	Sensitivity to noise and complex background variations

The comparison across Tables 1–3 highlights significant advances in deep learning approaches for plant disease diagnosis. While many models achieve high classification performance on benchmark datasets, their practical deployment is often constrained by factors such as computational complexity, large memory requirements, and limited robustness under diverse environmental conditions.

Transfer learning methods, including DenseNet121, MobileNetV2, and EfficientNet variants, have demonstrated strong performance. Nevertheless, their high number of parameters, susceptibility to overfitting, and relatively longer inference times restrict their suitability for edge devices or mobile systems commonly used in precision agriculture. Models incorporating attention mechanisms, domain-adversarial loss functions, or feature fusion show enhanced accuracy in controlled settings, but they introduce additional architectural complexity and often require extensive fine-tuning, which may limit generalizability across different crops and field conditions.

Cascaded and hybrid architectures combining CNNs with RNNs, U-Nets, SVMs, KNNs, or graph-based networks have been proposed to capture more intricate spatial and temporal patterns. While these architectures can provide superior feature representation and improved robustness, they generally involve higher computational overhead and slower inference times, constraining their applicability for real-time field deployment.

Overall, although the surveyed models demonstrate impressive results on laboratory and benchmark datasets, several limitations remain: dependency on small or imbalanced datasets, high model complexity, and sensitivity to domain shifts between controlled and field images. These observations suggest that while deep learning techniques have made substantial progress, further research is required to enhance model efficiency, robustness, and adaptability for real-world agricultural applications.

4.5 | Cascaded and Hybrid Models for Plant Leaf Diseases Detection

Evaluation of plant leaf disease detection models extends beyond mere accuracy metrics to include robustness, generalization, and practical deployment considerations. Standard evaluation protocols commonly involve dataset splitting into training, validation, and testing subsets, often complemented with cross-validation techniques to mitigate overfitting and assess model stability [7]. However, significant variations exist across studies regarding dataset size, class distribution, image resolution, preprocessing pipelines, and augmentation strategies, which can substantially influence reported performance metrics [56], [58], [61]. Consequently, direct comparison of reported accuracy across models should be interpreted with caution [56].

Deployment constraints represent another critical dimension, particularly for applications in resource-limited agricultural environments. Lightweight architectures, such as MobileNetV2, SqueezeNet, and EfficientNet variants, have been proposed to reduce computational cost and memory footprint while maintaining acceptable accuracy levels [9], [10]. These models facilitate edge deployment on mobile devices or embedded systems, enabling real-time disease monitoring directly in the field [12], [13]. In contrast, deeper or hybrid models incorporating attention mechanisms, cascaded CNN-RNN architectures, or graph-based modules often achieve higher accuracy but incur substantial latency, energy consumption, and memory requirements, limiting their suitability for low-resource environments [43], [44], [45].

Real-world applicability also depends on model robustness under varying field conditions, including lighting, occlusion, leaf orientation, background clutter, and disease severity [56], [57]. Studies have demonstrated that models trained solely on controlled datasets, such as PlantVillage [45], may exhibit reduced generalization when applied to images captured under natural conditions. Techniques including data augmentation, synthetic image generation via GANs, attention-based feature selection, and domain adaptation have been employed to enhance model resilience against such variations [34], [59].

Furthermore, deployment in real-world agricultural scenarios requires consideration of user accessibility and integration with IoT-based monitoring systems, enabling automated data acquisition and feedback for precision agriculture [12]. Hybrid approaches combining lightweight CNNs with autoencoders or sequential models have shown promise in balancing accuracy with edge-deployability, though these solutions may still be sensitive to noise or extreme environmental variability [41], [43].

In summary, comprehensive evaluation of plant disease detection models must integrate multiple criteria, including accuracy, computational efficiency, edge deployability, and robustness under realistic field conditions. Addressing these factors collectively ensures that developed models are not only scientifically robust but also practically applicable in precision agriculture contexts [12], [56].

5 | Challenges

Identification and detection of plant leaf diseases are influenced by several factors that affect the performance, robustness, and deployability of deep learning models. This section summarizes the main challenges reported in the studies reviewed (Refs. [22]–[55]) and discusses potential mitigation strategies.

5.1 | Limited Datasets

Deep learning models rely heavily on large, diverse datasets for effective training. Many studies utilize public datasets such as PlantVillage [45], [43] or custom datasets [47], [48], but small dataset size or domain-specific collection can limit generalization [47], [48]. For example, PlantVillage provides standardized images of multiple crops and disease classes [45], but models trained on this dataset may underperform in real-field conditions due to domain shift [43], [47].

To mitigate data scarcity, researchers have applied data augmentation, synthetic image generation via GANs [22], and transfer learning [37], [44], which have proven effective in improving robustness and generalization across different crops and disease types.

5.2 | Class Imbalance

Imbalanced datasets, where some disease classes have significantly fewer samples than others, are common in plant disease datasets [24], [35]. Models trained on such datasets may bias predictions toward majority classes, reducing accuracy for minority classes.

Techniques such as resampling [24], class weighting [35], and augmentation or GAN-based synthetic image creation [22], [28], [39] have been employed to address this issue, demonstrating improved classification for underrepresented diseases.

5.3 | Image Enhancement, Region Extraction, and Symptom Differentiation

Variations in illumination, noise, and image resolution affect feature extraction and classification accuracy [34], [36], [40]. Disease symptoms may blend gradually into healthy tissues, making early-stage detection challenging.

Methods like ROI extraction, image enhancement, and feature fusion [36], [40] have been applied to emphasize relevant regions and improve symptom differentiation, while attention-based mechanisms help focus the model on disease-affected areas [34].

5.4 | Early Lesions of Small Size

Small lesions are crucial for early disease detection but can be lost during pooling or down-sampling operations in CNNs [34], [62]. Integrating attention mechanisms [34] or hybrid CNN architectures [38], [41] improves sensitivity to subtle symptoms, allowing accurate detection even for early-stage diseases.

5.5 | Overfitting and Underfitting Problem

Complex deep learning models may overfit to limited training data or underfit when unable to capture relevant patterns [33], [35], [36]. Mitigation strategies include:

- Early stopping during training [35]
- Checkpointing best-performing models [33]
- Lightweight architectures to reduce parameter overcapacity [32], [44]

5.6 | Challenges in Fast and Efficient Detection of Plant Diseases

Deep learning models often require significant computation, limiting real-time applicability and edge deployment [25], [29], [42], [44]. Lightweight and efficient architectures such as MobileNetV2-based models [24], [44], Convolutional Autoencoder hybrids [41], and depthwise separable convolutions [44] balance speed and accuracy, enabling deployment in resource-constrained agricultural environments.

5.7 | Visual Ambiguity and Localization Challenges in Plant Diseases Detection

Certain plant species and diseases exhibit similar leaf morphology or co-occurring symptoms, complicating detection [43], [51], [55]. Techniques such as feature fusion, graph-based modeling, and multi-branch CNNs [54], [55] help models differentiate visually similar diseases. Attention-based mechanisms ([34], [44]) and cascaded architectures [43], [53] improve localization and robustness in challenging visual scenarios.

6 | Conclusion and Future work

This survey has provided a comprehensive review of recent advances in plant disease detection using deep learning techniques, emphasizing the strengths, limitations, and practical challenges associated with their deployment in smart agriculture. The critical importance of early disease detection is highlighted, as timely interventions can significantly reduce crop loss and enhance food security [22, 23, 43].

A comparative analysis of various models, including conventional deep learning architectures, pre-trained networks, enhanced CNN models, and hybrid frameworks, reveals that while many approaches achieve high classification accuracy, they frequently encounter issues such as computational inefficiency, increased latency, and limited generalization under real-world conditions [24, 44, 49]. Key challenges identified include:

- Limited dataset availability and diversity, constraining model generalization across crops and environmental conditions [45, 47, 48].
- Class imbalance, which negatively affects predictive performance for minority disease classes [22, 24, 35].
- Visual ambiguity and symptom localization, where overlapping or hidden disease signs complicate accurate detection [34, 43, 55].
- Detection of early-stage diseases, where small lesions may be missed during feature extraction or down-sampling [34, 44].
- Resource constraints, as high-performance models often require substantial computational power, limiting deployment on mobile or edge devices [44, 32, 46].

Prioritized research directions are recommended as follows:

1. Development of lightweight and robust architectures: Emphasis should be placed on efficient CNNs, hybrid models with attention mechanisms, and residual networks capable of handling high-resolution leaf images while reducing inference time [24, 34, 44, 51].
2. Dataset expansion and standardization: Future work should focus on creating large-scale, diverse datasets that include multiple crop species, field conditions, and mixed infections. Strategies may involve citizen science initiatives, crowd-sourced image collection, and synthetic augmentation using GANs [22, 23, 39, 56].
3. Deployment scenarios: Models should be evaluated for practical deployment, including mobile applications, IoT-enabled sensors, and UAV-based platforms, with benchmarks that reflect real-field variability such as lighting, occlusion, and overlapping leaves [9, 12, 44].
4. Interpretability and explainability: Incorporating methods such as saliency maps, Grad-CAM, and feature visualization is essential to improve user trust, model transparency, and actionable decision-making in agricultural contexts [43, 54, 55].
5. Comprehensive evaluation protocols: Establishing standardized metrics, benchmark datasets, and evaluation pipelines will guide future research and enhance reproducibility, allowing fair comparison across models and deployment scenarios [7, 56].

It is important to acknowledge the limitations of this survey itself. The review primarily considers studies published in English, which may introduce a language bias. Additionally, the literature search was confined to selected databases IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar, potentially excluding relevant studies from other sources. The survey mainly focuses on CNN-based architectures, with limited coverage of transformer-based or other emerging deep learning models. Recognizing these constraints provides context for interpreting the findings and highlights opportunities for more inclusive and comprehensive future reviews [7, 56].

Furthermore, future research should also consider data ethics, privacy, and user-centered design to ensure responsible deployment. This includes evaluating the potential consequences of misdiagnosis, integrating human–AI interaction strategies, and designing interfaces accessible to farmers [6, 12]. Addressing these aspects will enhance real-world applicability, trust, and adoption of deep learning-based plant disease detection systems.

By addressing these prioritized directions, future research can bridge the gap between algorithmic development and practical application, ultimately maximizing the impact of AI in sustainable and precise agricultural disease management [22, 43, 44].

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Ethical Approval

This article is a survey and does not involve any experiments with human participants or animals.

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