Deep Learning in Precision Phytopathology: A Comprehensive Survey of CNN Architectures for Disease Detection and Severity Quantification

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Deep Learning in Precision Phytopathology: A Comprehensive Survey of CNN Architectures for Disease Detection and Severity Quantification

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Abstract

Plant diseases are a major threat to the global agricultural productivity causing considerable yield losses and economic damage. Recent developments in Artificial Intelligence (AI) and specifically in Deep Learning has led to a revolution in the diagnosis of plant diseases with automated and scalable analysis of the crop images. This review offers an extensive synthesis of Convolution Neural Network (CNN) architectures engineered in precision phytopathology and mainly aimed at disease detection, classification, localization, and severity quantification. Following a systematic literature review using PRISMA methodology, this paper reports a structured taxonomy of CNN-based methods including classical classification networks, object detection networks and semantic segmentation models from 131 peer-reviewed articles. The review compares popular architectures like ResNet, EfficientNet, Yolo and U-net, highlighting their performance characteristics, accuracy-efficiency trade-offs, as well as suitability to real-world deployment. Findings show that although CNN based systems hold a high diagnostic accuracy in controlled settings, there are still issues especially related to generalization, dataset availability, and field level robustness. Emerging directions such as hybrid CNN-Transformer models, multimodal sensing and edge deployment are found as critical enablers for next-generation precision phytopathology systems for sustainable and data-driven crop disease management.

Keywords: Convolutional Neural Networks; Precision Agriculture; Plant Disease Detection; Severity Quantification; Computer Vision; Deep Learning; Systematic Literature Review

1 Introduction

The management of plant diseases is currently experiencing a paradigm shift in methodologies due to the rapid development of sensing technologies, artificial intelligence and data-driven agricultural systems. Population growth, climate variability and increased intensity of crop production continue to strain global food security, and plant pathogens are estimated to cause annual yield losses of 20-30% globally, corresponding to multi-billion-dollar economic impacts [1], [2]. In addition to the decrease in yield, the poor diagnosis of diseases slows down response, promotes the overuse of agrochemicals, negatively affects the environment, and increases the chances of local epidemics [3]. The combination of these issues highlights the need to have correct, scalable and timely disease diagnosis as a pillar to sustainable agriculture and agri-food systems with resilience.

Traditionally, the diagnosis of plant disease has been based on visual field scouting by specialists. Although this model is useful, it is subjective in nature, labour intensive and cannot easily be scaled at large or highly differentiated agriculture systems [4]. The reliability of the diagnostic technique is also limited by the fact that symptoms overlap across diseases, the intensity of light, and the phenological variation of crops [5]. Precision agriculture has brought about a new paradigm of quantitative, spatially explicit disease surveillance and a combination of Internet of Things (IoT) sensors, autonomous platforms, geospatial technologies, and high-resolution imaging systems RGB, multispectral, hyperspectral, and thermal sensors [6]. These technologies enable the acquisition of large-scale continuous images with smartphones, unmanned aerial vehicles (UAVs), and ground-based robots, which are the basis of the data of precision phytopathology. However, the usefulness of such systems is crucially dependent on the computational models which are able to generate significant diagnostic information out of high dimensional visual data subjected to real-world working conditions [7].

In this analytical environment, deep learning, especially convolutional neural networks (CNNs), has become the paradigm of image-based analysis of plant diseases [8]. CNNs can learn hierarchical features automatically, achieving the ability to detect complicated spatial structures in the form of lesion morphology, texture anomalies, and disease distributions without considering any handcrafted features [9]. Transfer learning also expands the applicability of CNN in agriculture, reducing the constraints of labeled data, and the generalization of cross-crops [10]. As Figure 1 illustrates, CNN-based pipelines are typically divided into disease detection and classification, which has been widely researched [11], and disease severity quantification, which is a relatively underrepresented field of study despite its direct connection to treatment decisions and estimation of the loss incurred [12].

To fill this gap, this Systematic Literature Review aims at presenting a systematic taxonomy and a comparative review of CNN designs in both disease detection and severity quantification and focuses on architectural design decisions, transfer learning, handling class imbalance, and severity-specific evaluation metrics. The review compiles peer-reviewed publications over the last five years (2021-2025), in accordance with current methodological and deployment-oriented developments in the field of precision phytopathology.

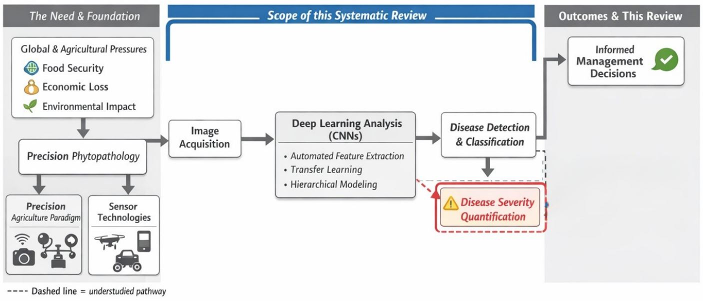

Fig. 1 Conceptual landscape of deep learning for plant disease diagnosis

2 Methodology

The review is based on the PRISMA 2020 (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) guidelines. PRISMA presents a uniform structure of comprehensive evidence synthesis, and it focuses on transparent reporting of all stages of identification, screening, eligibility assessment, and inclusion. It is essential to use in deep learning-oriented review studies, where methodological heterogeneity may compromise reproducibility, as well as comparative validity.

2.1 Systematic Search Strategy

An extensive search was carried out through a major bibliographic database highly reputed in the publication of research of good quality in computer vision, artificial intelligence, and agricultural sciences to provide multidisciplinary coverage. Scopus database was chosen, due to its broad area of interdisciplinary coverage, strong citation indexing and its comprehensive coverage of science, engineering and agriculture. The time frame covers the literature published between 2021-2025.

The final search strings were designed as the result of an iterative three-stage process: exploration, expansion, and refinement. Final Boolean strings were created with equal sensitivity and specificity: The resulting Boolean strings were modeled to have a desired sensitivity and specificity, as follows:

(”plant disease*” OR ”crop disease*” OR ”leaf disease*” OR “phytopathology”) AND (”deep learning” OR ”convolutional neural network” OR ”CNN”) AND (”detect*” OR ”classif*” OR ”severity” OR ”quantif*”) AND (”image-based” OR ”computer vision”)

2.2 Study Selection Process

The selection of the study adhered to the PRISMA 2020 flow diagram Figure 2, where the number of identified records, screened, eligible, and included in the review are given, and the causes of exclusions at each of the stages are reported.

Both title/abstract and full-text screenings of the studies were assessed by comparison with a list of predetermined inclusion and exclusion criteria, which are described in Table 1.

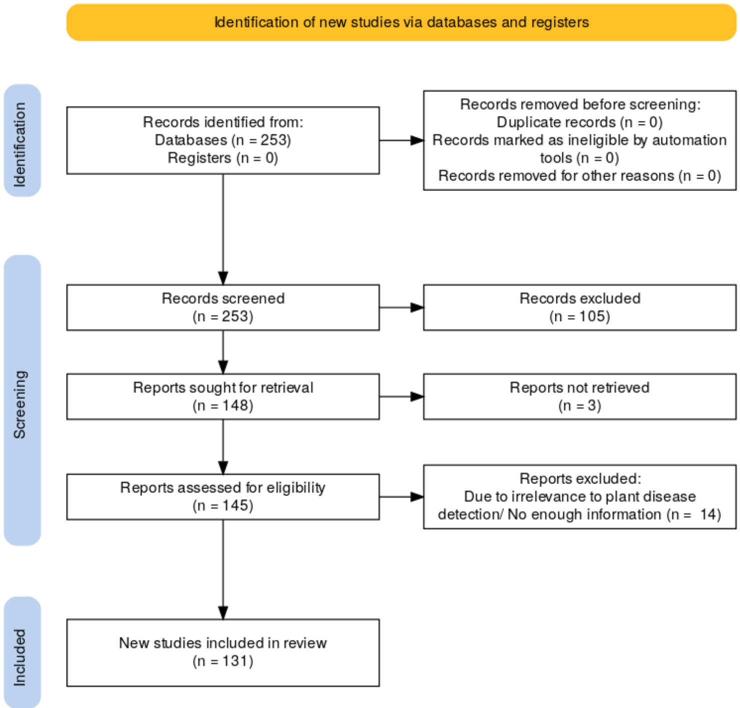

Fig. 2 PRISMA Flow Diagram

Table 1 Inclusion and Exclusion Criteria

Criterion	Include	Exclude
Methodology	Primary application of CNN architectures	Non-CNN methods (SVM, hand-crafted features)
Focus	Disease detection, classification, or severity assessment	General plant stress, nutrient deficiency, and species identification
Data Type	Visible-range (RGB), multispectral, or hyperspectral images	Non-imaging data (genomic, meteorological, audio)
Technical Detail	Clear description of CNN architecture, dataset, and evaluation.	Insufficient methodological information
Publication Type	Peer-reviewed articles	Reviews, books, theses, preprints, editorials

3 Taxonomic Framework of Deep Learning Architectures for Plant Disease Phenotyping

The high rate of deep learning applications in plant pathology has resulted in a wide variety of neural network designs, with each designed to meet certain diagnostic goals and deployment considerations [13]. A systematic model selection requires a structured taxonomy to support it. As shown in Figure 3, deep learning systems for plant disease phenotyping can be structured into five major families, ranging from image-level classification to pixel-level severity estimation. This taxonomy facilitates the correspondence of the phenotyping goals, information available and operational demands, and guides the efficient and context sensitive model design.

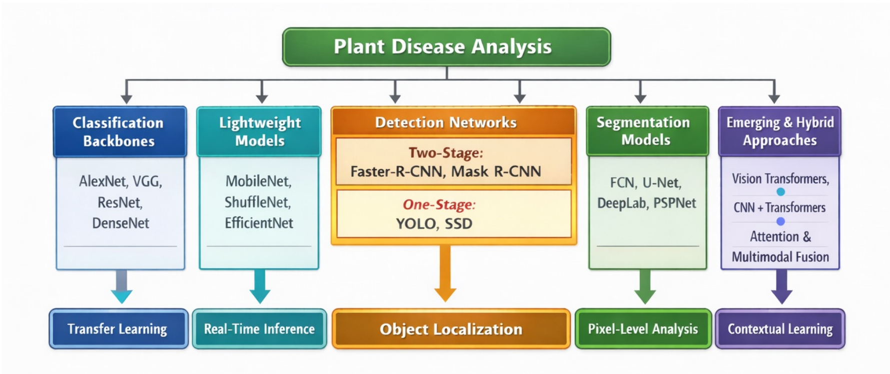

Fig. 3 Taxonomy of Deep Learning Architectures for Plant Disease Analysis

3.1 Diagnostic Pipelines Task-Architecture Alignment

The architectural selection mainly depends on the target analytical task of the diagnosis pipeline of the disease. Figure 4 visualizes typical phenotyping tasks along with their families of deep learning models with the focus on representative models and their functional capabilities. This type of alignment takes advantage of task-relevant inductive biases, which guarantee efficient utilization of computational resources and maximizes the diagnostic performance [14]. As an example, classic CNN backbones prove to be useful in image classification and transfer learning tasks [15], [16], while pixel-level severity prediction requires segmentation architectures trained on dense spatial prediction [17]. This task-based mapping forms the basis in the development of diagnostic systems that would be scaled and accurate.

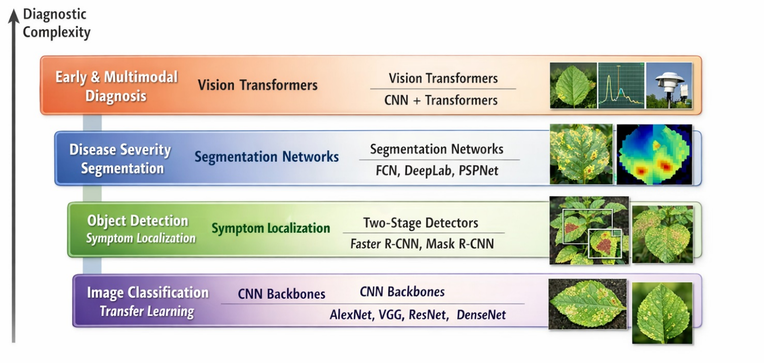

Fig. 4 Tasks and Deep Learning Architectures for Plant Disease Analysis

3.2 Architectural Families and Phytopathological Applications

Classical CNN backbones continue to play central roles in the recognition of plant diseases because they are effective when having limited labeled data. One of the most widely reported transferable feature extractors is pre-trained architectures, including ResNet, VGGNet, and DenseNet, with the variants of ResNet, specifically ResNet-50, being classified as highly accurate, high-efficiency, and generalized [18].

Lightweight models such as MobileNet and ShuffleNet enable deployment of computationally efficient models on resource-constrained systems for large-scale, real-time crop monitoring applications, through the use of computationally efficient design decisions [19], [20].

The purpose of object detection architecture is to solve the problems where spatial localization of disease symptoms is needed. Two-stage detectors focus on localization accuracy [21], whereas one-stage detectors focus on inference speed, and a trade-off of accuracy versus latency in field use arises [22].

The quantitative severity quantification depends on semantic segmentation models like U-Net, FCN, and DeepLab, which have pixel-precise lesion segmentation. Specifically, the encoder-decoder architecture of U-Net with skip connections is useful in terms of maintaining spatial features, and thus the severity estimation can be objective and reproducible [23].

Emerging architectures build up the diagnostic capability with the help of more extensive contextual modeling and data integration. Long-range dependencies are represented by Vision Transformers and hybrid CNN-Transformer architecture [24], [25], and attention-enhanced CNNs help to enhance robustness in the complex field setting [26]. The multi-modal fusion networks are also designed to promote early and accurate diagnosis, by incorporating complementary sensing modalities to the RGB image [27], [28].

3.3 System-Level Integration and Performance Considerations

Effective deployment cannot be achieved by architecture choice only. As Figure 5 summarizes, the overall system performance is affected by the interactions among the aspects of the deep learning lifecycle, such as the quality of data, preprocessing, complexity of models, and their constraints with deployment [29]. The strong datasets, proper augmentation strategies, and the right management of the trade-off between the capacity of the model and the real-time feasibility is essential [30]. Furthermore, optimized training methods and model interpretability are crucial towards reliability, confidence among the stakeholders and realistic incorporation into the agricultural decision-support systems [31].

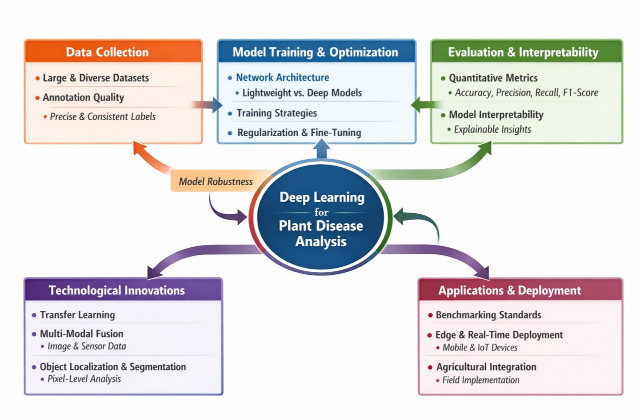

Fig. 5 Performance Factors and Trade-offs in Deep Learning for Plant Disease Analysis

4 Disease Detection and Classification Approaches

Plant disease analysis based on deep learning may be divided into three major paradigms, namely classification, detection, and segmentation. These paradigms vary in terms of granularity of prediction, complexities of computation and applicability to agronomics. In accordance with studies based on the synthesis of the collected data, this section critically reviews representative contributions in each category, focusing on architectural trends, use of datasets, and reported performance.

4.1 Classification-Based Studies on Plant Diseases

The most studied task of CNN-based phytopathology is classification. The goal is to classify an input image, which is usually a leaf, into a few disease categories [32]. The majority of studies follow the approach of transfer learning by using ImageNet-pretrained backbones and assess performance in terms of accuracy as the main metric.

There is an evident supremacy of DenseNet, EfficientNet, ResNet, Inception, and VGG variants. Accuracies of studies using controlled datasets including PlantVillage are often over 97% with a number of ensemble frameworks exceeding 99% Table 2. Nevertheless, the performance is likely to drop when models are tested on field-collected data because of the complexities of the background, variations in illumination, and obstruction.

Table 2 Classification-based plant disease studies

Ref	Model	Dataset	Accuracy	Precision	Recall	F1-Score
[33]	DenseNet201	Kaggle	96%	90%	90%	90%
[34]	VGG16, ResNet50, and InceptionV3	Kaggle	96.80%	96.70%	96.40%	96.50%
[35]	DenseNet121, ResNet50, EfficientNetB0	Kaggle	99.88%	-	99.89%	99.88%
[36]	BO-IKM	Plant Pathology	95%	91%	-	90%
[37]	RLDC-CNN	Mendeley and Kaggle	99.15%	99.15%	99.13%	99.13%
[38]	SSMAN	Field-collected	98.30%	97.56%	97.56%	97.13%
[39]	ResNeXt	Field-collected	99.22%	92.87%	91.97%	90.95%
[40]	EfficientNet-B0	PlantVillage, PlantDoc	98.85%	88%	87%	93%
[41]	CNN-based	Field-collected	97.04%	-	-	-
[42]	EfficientNetB0-Attn	PlantVillage, PlantDoc	99.39%	99%	99%	99%
[43]	CNN + RNN + LTCN hybrid	PlantVillage	97.15%	97.16%	97.09%	97.11%
[44]	Lightweight CNN	PlantVillage, ESCA	95.24%, 98.10%	-	-	-
[45]	Two-step CNN	PlantVillage	99%	99%	99%	99%
[46]	Lightweight CNN	Field-collected	96.50%	-	-	-
[47]	Modified Inception-V3	PlantVillage, PlantDoc	99.48%, 76.91%	-	99.23%, 76%	-
[48]	VGG16, VGG19, Xception	PlantVillage	99.82%	100%	100%	100%
[49]	MUTPSO-CNN	Kaggle	97.35%	97.10%	96.41%	96.70%
[50]	AlexNet, VGGNet, ResNet	ImageNet, Outex, PlantVillage	97.44%	95.54%	95.77%	95.65%
[51]	CNN-SEEIB	PlantVillage	99.79%	99.70%	99.72%	99.71%
[52]	Shallow CNN + Transfer Learning	Field, PlantVillage, Mendeley	95.31%	-	-	-

4.2 Detection-Based Studies on Plant Diseases

Detection-based methods expound classification through localization of areas of disease in the form of bounding boxes. This paradigm applies especially in the context of real-time monitoring, smart agriculture applications when there are several leaves or lesions on a single frame.

Most of the detection studies utilize YOLO (v5-v8) and Faster R-CNN structures Table 3. One-stage detectors (YOLO variants) prevail because they achieve a tradeoff between performance and inference speed. Mean Average Precision (mAP) is normally used to report performance.

Table 3 Detection-based plant disease studies

Ref	Model	Dataset	Performance (mAP)
[53]	Inception v4, YOLOv8	PlantVillage, Kaggle	86%
[54]	Optimized RFCN	Field-collected	93.80%
[55]	YOLOv10	Roboflow	88.85%
[56]	SEDCN-YOLOv8	Field-collected	75.1%
[57]	BED-YOLO	Field-collected, PlantVillage	87.4% to 91.3%
[58]	LT-YOLO	Roboflow	90.9%
[59]	RSD-YOLO	Field-collected	88.5%
[60]	YOLO-SSM	Field-collected, Public	89.7%, 68.5%
[61]	YOLOv5s-SE7	Field-collected	90.5%
[62]	MAF-YOLOv8	Field-collected	91.7%

4.3 Segmentation-Based Studies on Plant Diseases

Segmentation offers the pixel level definition of diseased areas and the estimation of disease severity which is a crucial parameter to accurate spraying and predicting the yield. Segmentation is more computationally expensive and has better interpretability than classification and detection.

The majority of segmentation works adopt encoder-decoder networks, including U-Net, Attention U-Net, Mask R-CNN and DeepLab V3+. Intersection over Union (IoU) or Dice coefficient is commonly used to examine performance as presented in Table 4.

5 Deep Learning for Disease Severity Quantification

Deep learning (DL) approaches have emerged as the new frontiers in quantitative plant disease determination replacing binary detection with objective reproducible severity estimations [12]. The existing methodologies can be broadly divided into classification-based grading, segmentation-based measurement and regression-based continuous prediction represented in Figure 6, and each of them can serve as the reflection of various assumptions regarding disease manifestation and the annotation granularity [70].

Table 4 Segmentation-based plant disease studies

Ref	Model	Dataset	Performance
[63]	SUNet	JMuBEN, JMuBEN2	IoU = 97.80%
[64]	DeepOverlay L-UNet	Citrus leaf images	IoU = 93.34%
[65]	CLAHE-Mask R-CNN, DeepLabV3+	Field-collected	PA 94.03%, 97.41%
[66]	U-Net (VGG encoder)	Field-collected	IoU = 0.9569
[67]	L*a*b* color-based segmentation	PlantVillage	Accuracy 98.63%
[68]	SegPPD-FS	SegPPD-101	mIoU 71.19% - 72.74%
[69]	YOLOv8, DeepLabV3, CNN, U-Net	PlantVillage	IoU 0.80-0.87

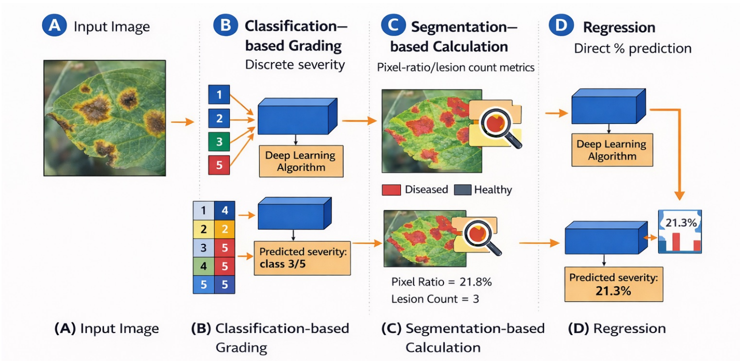

Fig. 6 A conceptual overview of deep learning approaches for disease severity quantification

5.1 Classification-Based Severity Grading

Classification-based grading poses the disease severity estimation as an ordinal multi-class classification task, the images are assigned to a discrete severity level, usually based on the Horsfall-Barratt (HB) scale [71]. CNN architectures trained on large-scale datasets are fine-tuned to acquire a set of discriminative visual representations that are associated with an increasing level of disease severity, including the density of lesions, color saturation, and spatial dispersion [72], [73].

Mathematically, an input image x, is presented to the model, which forecasts a severity category $\hat{y} \in \{0, 1, \ldots, k\}$ via:

$$\hat{y} = \arg\max_{k} p(y = k \mid x), \tag{1}$$

Where K represents the highest grade of severity.

This method is computationally effective and is consistent with expert-based field assessments. Nevertheless, it is subject to label subjectivity, class imbalance, and coarse granularity, especially in cases where the progression of the disease is continuous, not stage-based [74].

5.2 Segmentation-Based Severity Calculation

The methods based on segmentation offer pixel-level quantification of disease, which is more spatially accurate and biologically interpretable than classification-based grading [75].

5.2.1 Semantic Segmentation

Semantic segmentation models, including U-Net [76] and DeepLabV3+ [77], assign each pixel the label of either a healthy or diseased tissue. The severity of the disease is then calculated as:

$$\text{Severity}(\%) = \frac{N_{\text{infected}}}{N_{\text{leaf}}} \times 100 \tag{2}$$

Such models are useful to describe irregular lesion boundaries and focal patterns of symptoms especially when imaging is under controlled conditions [73]. However, their performance is highly reliant on the quality of pixel-wise annotations, which is expensive to acquire on a large scale.

5.2.2 Instance Segmentation

The most notable objects of instance segmentation frameworks (primarily, Mask R-CNN) are object detection with a focus on a specific disease manifestation (i.e., pustules, lesions, or spots) [78]. The severity may be estimated using lesions counts, lesion area sums, or lesion size distribution modeling [79], [80].

The paradigm is especially appropriate in the case of diseases with discrete symptoms (e.g., rusts or blights) and allows conducting epidemiological analysis on a fine scale [81]. Nevertheless, overlapping lesions and high-density regions of infection may worsen accuracy of instance separation.

5.2.3 Regression-Based Severity Estimation

Regression-based methods are used to directly predict a continuous severity measure, which is usually given as Percentage of Infection (POI) [82]. The models reduce losses like mean squared error (MSE) or mean absolute error (MAE) to obtain smoothing severity estimates that are more representative of gradual progression of diseases [83]. Although regression does not have the bias of discretization, it is vulnerable to annotation noise and must have uniform ground-truth measurements of severity.

6 Comparative Analysis and Synthesis

In this section, a synthesis of evidence in the literature is conducted to determine systematic patterns of performance, architectural trade-offs, dataset biases, and implementations of CNN-based methods in precision phytopathology. The analysis combines the results of model families, crop, tasks, and computational constraints to provide knowledge on making decisions in methodology selection and practical use instead of repeating the results of individual studies.

6.1 Architecture-Wise Comparative Trends

To consolidate patterns of architectural performance, Figure 7 provides task-architecture-trade-off framework, which summarizes classification, detection, segmentation, and hybrid modeling families.

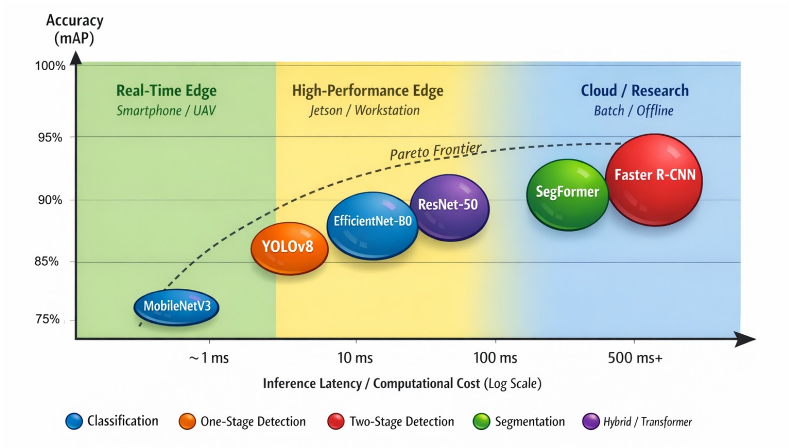

Fig. 7 Task-architecture-performance trade-off framework

To obtain image-level disease classification, EfficientNet variants are shown to achieve the most desirable accuracy-parameter efficiency tradeoff, with a very high accuracy of well over 90% under controlled settings, and with small architecture sizes [84]. This efficiency renders them specifically applicable to the scaled agricultural surveillance schemes.

ResNet backbones (ResNet-50 and ResNet-101 in particular) continue to be the most prevalent transfer-learning model, as they are architecturally more stable and cross-crop generalization is much more reliable [85], [86]. DenseNet architectures are more resilient to the data-scarcity setting, where dense feature reuse can alleviate overfitting and maintain the performance on the underrepresented crops and regions [87].

Localization of the disease implements a serious accuracy-speed trade-off. Two-stage detectors like Faster R-CNN demonstrate a better localization accuracy (mAP 0.5 = 0.88) but are computationally expensive to execute in real-time [88]. One-stage detectors, especially YOLO-based architectures, on the other hand, can reach competitive results (mAP@0.5 0.80-0.86) and allow real-time inference on edge devices, which is a beneficial factor in in-field monitoring [89].

U-Net and its variants are the most prevalent in the literature to generate pixel-level lesion localization and estimate severity with IoU scores of over 0.80 in laboratory settings [90]. Nevertheless, the observed performance deterioration in the natural field variability highlights the sensitivity to the change of the illumination and background clutter. The improved encoder-decoder models that include attention and multi-scale aggregation have shown better robustness and boundary precision, especially to irregular morphology of lesions [91].

CNN-Transformer architectures comprise hybrid networks that combine convolutional local feature extractors and global contextual modeling [92], [93]. Whereas pure Transformer models are still data-intensive and not as effective on small agricultural data, hybrid designs have shown competitive accuracy compared to EfficientNet and ResNet, especially in modeling spatial disease patterns [94], [95]. However, the high level of computation prevents its use in agricultural settings with limited resources.

6.2 Crop-Wise and Disease-Wise Distribution Patterns

Systematic bias pervades dataset composition and model validation. The visualization of crops in CNN-based studies of plant diseases in Figure 8 shows structural imbalance and long-tail distribution.

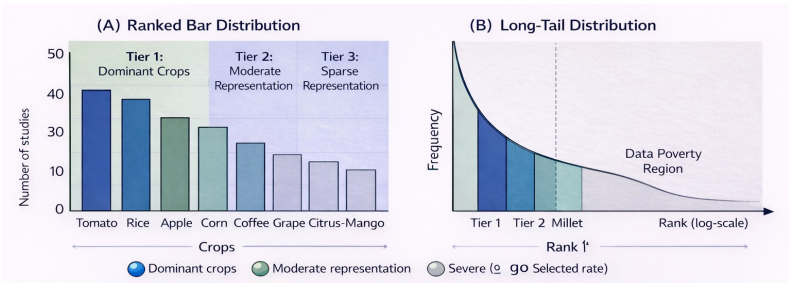

Fig. 8 Crop-wise distribution and long-tail bias in CNN-based plant disease research

6.2.1 Dominance of Major Crops

The dominance of empirical evaluation is held by a tiny fraction of crops. Tomato (Solanum lycopersicum) is the most studied crop, followed by rice (Oryza sativa), apple (Malus domestica), and maize (Zea mays) as indicated in Figure 8. Their success has been attributed to their economically significant, visually characterized foliar symptoms, a short growth period and the existence of curated datasets.

Rice-related studies often focus on blast, bacterial blight, and sheath blight, which are related to its food security importance on the global level and increased attention to field-acquired images [96], [97]. The UAV-based methods and in-field data are increasingly used in the Apple and maize studies to determine the operational robustness [98], [99], [100].

6.2.2 Long-Tail Crops and Limited Coverage

In addition to prevailing crops, there is the development of a sharp long-tail distribution. Crops such as grape, citrus, mango, bean, pea, cucumber and chili are not widely represented in the literature as depicted in Figure 8. Crops that are considered regionally critical, such as cassava, sorghum, millet and cashew, are largely underrepresented or not present at all.

Such an imbalance indicates structural dataset poverty and regionalization, especially on the agricultural systems with tropical and smallholder predominance [101]. This limitation is also increased by perennial and plantation crops, where the dynamics of diseases over a long period of time and canopy cover are not adequately represented by CNN pipelines trained on short-cycle annual crops [102].

6.3 Single vs Multi-Stream CNN Architectures

Figure 9 compares structural dissimilarities among single-stream and multi-stream CNN Frameworks.

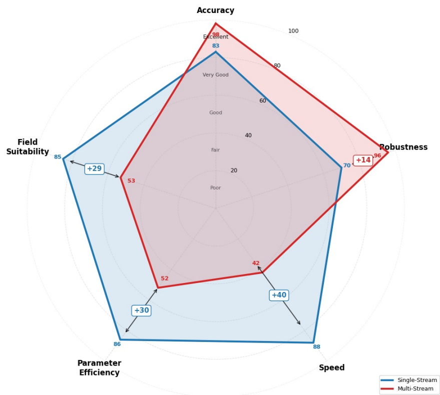

Fig. 9 Structural comparison between single-stream and multi-stream CNN architectures

6.3.1 Single-Stream Architectures

Single-stream CNNs utilize one convolutional pipeline to process input images, and this method remains the most popular because of its simplicity and reduced computational cost [103]. A large number of backbones, like ResNet [104], EfficientNet [105], and MobileNet [106] are used to attain high accuracy on well-studied crops in controlled settings.

In the case of localization, one-stage detectors with single streams (e.g., YOLO variants) can be used to perform inference in real-time on the field [59]. Nevertheless, robustness is reduced in the presence of illumination variation, occlusion, and in the early stages of symptom detection, which also indicates vulnerabilities to using one feature pathway [107], [108].

6.3.2 Multi-Stream Architectures

Multi-stream CNNs add parallel branches of feature extraction to obtain complementary features (texture, color, spatial context), and fuse them at intermediate or final stages [109]. According to the empirical evidence, steady improvements of 2-6% in F1-score or IoU are observed, especially in the multi-disease classification and severity estimation tasks [110], [111].

Multi-stream encoder-decoder models are beneficial in severity evaluation with respect to boundary delineation and lesion completeness in case of segmentation-based severity assessment [112], [113]. These performance improvements, however, come at the cost of more parameter counts as well as parameter inference latency, limiting deployment without model optimization strategies [114].

6.4 Computational Complexity and Deployment Considerations

The conversion of CNN-based diagnostics into usable agricultural system must compromise predictive quality with latency, power and hardware expenses. Figure 10 presents a deployment trade-off framework that combines the relationships of accuracy and latency with edge-clouds.

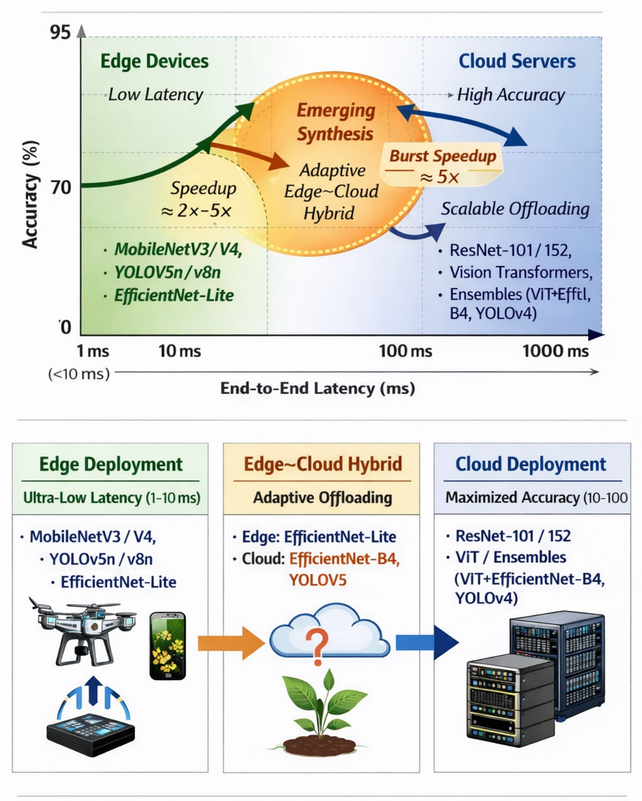

Fig. 10 Deployment trade-offs and system-level architecture for CNN-based plant disease diagnostics

6.4.1 Real-Time Feasibility

An accuracy-latency asymptote is a regularity that may be noted in Figure 10. Lightweight CNNs have been found to offer the most feasible trade-off to real-time agricultural applications [115]. MobileNet and compact EfficientNet architectures can be used to infer on-device smartphones, facilitating offline smartphone diagnostics for smallholder farmers [116].

In the case of UAV-based monitoring, the strong latency requirements are in favor of optimized one-stage detectors that are able to identify disease hotspots during flight [117]. Small backbones are used in the greenhouse settings to maintain constant low-power surveillance [118].

At some point, the complexity of a model does not yield proportional improvements in the reduction of latency; at that point, only a shallow improvement in field deployment is possible [119]. Common optimization methods, such as quantization, pruning, and knowledge distillation, are used to minimize the cost of computation without affecting predictive performance [120].

6.4.2 Edge vs Cloud Deployment Paradigms

Deployment strategies do not only constitute the technical decisions; they are socio-technical commitments. The deployment strategies are usually based on edge, cloud or hybrid paradigms.

Edge deployment is characterized by low latency, offline, and privacy of data [62], limited by some memory and computing capabilities [121]. Cloud systems are able to offer high capacity models, centralized updates, and scale elasticity, but are subject to network connectivity and bring in latency and cost factors [122].

There is growing support around the use of hybrid edge-cloud frameworks. In such systems, edge models which are lightweight are used to perform preliminary screening, while uncertain cases are sent to cloud-based edge models for analysis. Federated learning also enables collaborative model learning without centralized data aggregation, and it actively balances privacy with scalability [123].

7 Critical Challenges and Future Prospects

Despite rapid advances, the application of CNN-based systems in precision phytopathology is limited in terms of generalization, data scarcity, and system-level integration. This part summarizes the major limitations and presents evidence-based research directions.

7.1 Generalization and Domain Shift

The most common obstacles to real-world implementation are generalization, and domain shift, which is the decrease in model performance when trained on controlled laboratory environments to field environments because of changes in illumination, background clutter, growth stages, and sensor properties [124]. The empirical studies found that there is a significant reduction in accuracy when curated datasets are substituted with in situ agricultural imagery [125].

To close the gap between source and target domains, as in Figure 11, representation-level alignment schemes as well as data-centric augmentation schemes are required. The future studies must use clear cross-domain evaluation splits to guarantee ecological strength [124].

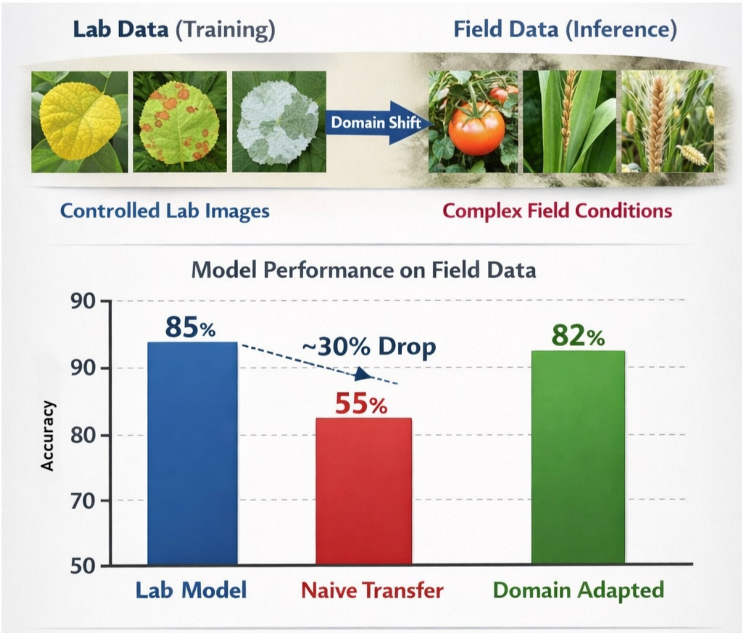

Fig. 11 Domain shift between laboratory and field environments and representative mitigation strategies

7.2 Few-Shot Learning for Emerging Diseases

Most CNNs require large labeled datasets, which cannot be achieved in the case of emergent or mutated pathogen. Few-shot and meta-learning methods seek to acquire transferable representations that can be learned by a small number of labeled instances [126]. Initial results have indicated higher adaptability across crops and diseases, but robustness in field conditions remains an open problem [127].

7.3 Multimodal Integration for Predictive Phytopathology

Vision-only systems have a high diagnostic accuracy and can be categorized as a reactive system, with the disease detected only when the symptom manifestations occur. Multimodal architectures can support a move toward a more anticipatory risk forecasting than a reactive diagnosis, as shown in Figure 12, combining images with weather and in-field sensor telemetry has supported short lead-time predictions of outbreaks (typically days to a week) [128]. In future studies, a combination of temporal modeling with the purpose of capturing disease-progression dynamics should be considered, such as Temporal Fusion Transformer (TFT) style architectures have already been successfully utilized in agricultural time-series forecasting and are a viable option to explicit progression modeling [129].

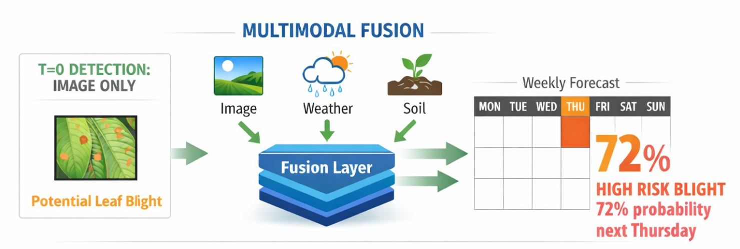

Fig. 12 Multimodal fusion framework integrating visual and environmental data for predictive phytopathology

Multimodal architectures, which include meteorological time-series and soil sensor telemetry can generate useful lead-time shifts of 3-7 days to aid in predicting pathogen threats, as well as early fusion of hyperspectral indices (e.g. NDVI, PRI) with thermal imagery can achieve pre-symptomatic physiological stress; recent hyperspectral studies show detection of a disease prior to the emergence of visual symptoms [130]. Weather-forecast outputs are also late fused to help in probabilistic weather-forecast modeling and assist operational decision support [131].

The most important directions include temporal-fusion transformers, which explicitly represent disease-progression curves, causal-inference systems to dispose of the difference between correlation and environmental causation, and the quantification of the uncertainty at a variety level to support risk-based decisions [129].

7.4 Robotic Integration and Spot Spraying

One of the main frontiers is the bridging of the gap between perception and action. The integration of vision models with agricultural robotics facilitates autonomy, localized interventions, such as spot spraying, which invariably results in a reduction of up to 85-95% of herbicides and pesticides dispensation relative to conventional broadcast methods. Field trials reveal that CNN-controlled robots, e.g. OrcBOT [132] and VGG-based systems [133], are capable of treating infected plants with great accuracy at a selective level. However, there are still serious issues in real-time inference speed (an average of 42.6 ms/image), navigation across unstructured or uneven terrain and safety guarantees during human-robot interaction in farm settings.

7.5 Data-Centric Challenges and Dataset Scarcity

The absence of large-scale, diverse, and field acquired datasets, especially in regard to minor crops and developing areas, is a fundamental limit to progress. This data poverty increases bias, acts as a hindrance to generalization and constrains equitable impact. There are growing support in data-centric AI implementations, systematic dataset curation, standard procedures, weak supervision and federated learning, as the necessary supplements to architectural innovation [134], [135].

7.6 Explainable AI (XAI) in Phytopathology

Even with high predictive accuracy, deep CNNs are simply black boxes in nature, which prevents agronomic trust and regulatory acceptance [136]. Methods like saliency graphs, and Gradient-weighted Class Activation Mapping (Grad-CAM), which can be referred to as explainable AI (XAI), overcome this drawback by producing visualized explanations that ascribe predictions by a model on a given input attribute [137]. The techniques enable researchers to verify the presence of classifications based on corresponding pathological symptoms (e.g., lesions, chlorosis) and not confounding factors.

This principle is demonstrated in Figure 13, which provides a comparative analysis of Grad-CAM explanations of CNN-based disease classification. In the correct attribution scenario (A), the model concentrates on the symptomatic areas of lesions, providing a prediction of "Blight" with 96% confidence and a high degree of trust. On the other hand, the spurious attribution case (B) illustrates the effect of visual explanations to reveal the biases of the model: although 92% confident, the prediction is not based on plant tissue but background artifacts, which implies that it is not a reliable way to make decisions.

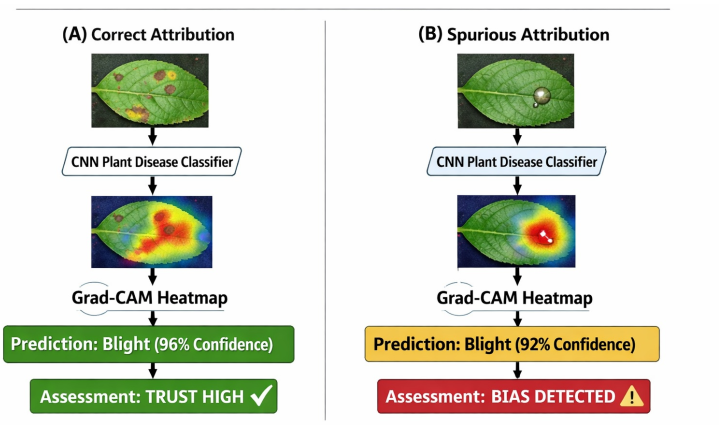

Fig. 13 Explainable AI workflow linking CNN predictions to lesion-level visual attribution

There are two purposes of such XAI applications in model validation. They facilitate expert validation of diagnostic logic and help identify spurious correlations that may undermine model generalization in different field conditions [138]. Such transparency is necessary in order to establish trust in automated diagnostic systems and fulfill future regulatory demands to have interpretable AI in agriculture.

7.7 Lightweight CNNs for Mobile and Edge Devices

Lightweight CNNs in scalable field deployment strike a balance between low latency, accuracy, memory and energy consumption. Architectures such as MobileNet, ShuffleNet, and EfficientNet-lite are able to deliver competitive performance through depthwise separable convolutions, compound scaling and hardware-conscious optimization. The real-time inference on smartphones and edge devices has been empirically verified to have trade-offs in accuracy that are modest, particularly when pruning, quantization, and knowledge distillation are used together [139]. Subsequently, future efforts should focus on hardware-and-task-specific compression and co-design in the detection and severity of diseases.

7.8 Benchmark Datasets for Severity Grading

The development of the severity quantification is impeded by the absence of a standardized, field-scale benchmark, which is labeled similarly (ordinal grades, pixel-based masks or continuous POI). Existing datasets are fragmented by crop, disease, and acquisition conditions, impeding fair comparison and reproducibility. It is supported by the fact that multi-crop, multi-region benchmarks, using expert-calibrated labels of severity, standardized metrics of evaluation (e.g., MAE/IoU), and explicit domain-shift splits are necessary [12], [140]. Benchmarks based on the community would enable strategy validation and translation at a faster pace.

8 Conclusion

The review provides an overview of evidence used to describe the development of CNN-based approaches to precision phytopathology covering disease detection, classification, and severity quantification. Taken together, these literatures have shown that CNNs have conclusively pushed the diagnostics of plant diseases beyond the subjective visual approach to automated, scalable, and objective methods, and outperforming traditional machine-learning pipelines based on handcrafted features.

A clear task-specific patterns are created in architectural terms. Disease identification with the help of transfer learning: classification backbones (e.g., ResNet-, EfficientNet, and DenseNet-based models) facilitate learning on an abstract level; spatial localization: object detectors (YOLO variants and Faster R-CNN) allow making an inherent trade-off between accuracy and latency; and pixel-level severity estimation: segmentation models (U-Net/DeepLab families) are necessary to align these capabilities with expert assessments. The next generation is hybrid, attention-enhanced, and multimodal, which provides better contextual reasoning and initial detection.

The key observation is the large gap between the laboratory and field performance. Laboratory accuracies often deteriorate in the presence of real-world variability (illumination, background clutter, cultivar diversity), which highlights that accuracy-based benchmarks are not adequate proxies of deployability. The main obstacles to impact are robustness, generalization and system integration.

Aspects toward which future development should focus include: (i) robustness-focused evaluation to balance between different field conditions; (ii) system-level integration, including connecting perception to decision support and actuation; (iii) data-centered in order to meet the demands of limited, diverse, and field-scale severity annotations, in particular underrepresented crops and regions; and (iv) socio-technical integration, including making it accessible, equitably distributed, and responsibly deployment.

In sum, CNNs have a promising future in plant disease diagnostics, which will eventually yield value of field-robust, data-centric, and inclusive systems that can transform the developments in AI to sustainable agricultural practices and a better food security.

Declarations

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