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Plant leaf disease detection and classification using convolution neural networks model: a review

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Abstract

Plants play a vital role in providing food on a global scale. Several environmental factors contribute to the occurrence of plant leaf diseases, leading to substantial reductions in crop yields. Nevertheless, the process of manually detecting plant leaf diseases is both time-consuming and prone to errors. Adopting deep learning technologies can address these challenges, and the efficacy of deep learning techniques in precision agriculture has been explored over the past decades. However, despite these applications, several gaps in plant leaf disease research still need to be addressed for efficient disease control. This paper, therefore, provides an in-depth review of the trends in using convolutional neural networks for leaf disease detection and classification. In addition, we also present the existing plant leaf disease datasets. It was found that convolutional neural network models, such as VGG, EfficientNet, GoogleNet, and ResNet, provide the highest accuracy in classifying plant leaf disease images. This review will provide valuable information for scholars who are seeking effective deep learning-based classifiers for plant leaf disease detection and classification.

Keywords Deep learning · Convolutional neural network · Plant leaf diseases · Object detection · Classification · Dataset

1 Introduction

According to the Food and Agriculture Organization (FAO), plant leaf diseases and pests pose a significant threat to global food security, accounting for 20–40% of global food production losses (Food and Agriculture Organization of the United Nations, n.d.). Furthermore, plant leaf diseases alone are estimated to be responsible for 13% of global crop yield loss (Ahmad et al. 2023a, b). These statistics emphasize the importance of early-stage plant leaf disease detection in reducing yield losses. Plant leaf diseases are mainly caused by pathogenic microbes, including fungi, bacteria, and viruses (Velásquez et al. 2018). However, farmers frequently fail to identify evolving pathological disorders at early stages

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because initial infections are not always visible. Additionally, the conventional detection process is time-consuming and inefficient for large farms. In the early 2000 s, computer vision-based, machine learning-based, and deep learning-based approaches were introduced to address conventional plant leaf disease detection and identification (Alex et al. 2012; Dutta et al. 2014; Huang 2007; Moshou et al. 2005). However, computer vision-based techniques work successfully only in simpler and controlled setups but struggle as operational conditions change (Hasan et al. 2020).

Machine learning-based plant leaf disease detection and classification techniques have gained significant popularity (Ngugi et al. 2021). Among these, supervised learning methods such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), K-Nearest Neighbour (KNN) algorithms, Artificial Neural Networks (ANNs), Naïve Bayes (NB), Decision Trees, Random Forests (RF), and Logistic Regression (LR) have been extensively employed for identifying various ailments such as leaf blotch, powdery mildew, and rust, alongside symptoms of non-biological stresses such as drought and nutrient deficiency (Anjna et al. 2020; Genaev et al. 2021; Mohanty et al. 2016). Agarwal et al. (2020) proposed a CNN-based tomato leaf disease detection (ToLeD) model that classifies ten diseases from tomato leaf images. However, the model achieved an accuracy rate of only 91.2%. Kumar et al. (2020) conducted a comparative analysis of the classification performance of four classifiers, namely SVM, KNN, Linear Discriminant Analysis (LDA), and ZeroR. The study classified unhealthy and healthy leaves using the Subtractive Pixel Adjacency Model (SPAM). The authors demonstrated that the SVM classifier yielded the highest accuracy rate of 92.12%, outperforming other classifiers. Chen, Yin et al. (2020) proposed a Group Method of Data Handling (GMDH)-Logistic model, which employs a multilayer perceptron to detect cucumber leaf diseases from a small-sized dataset. The model achieved an average recall of 86.67%, though its applicability may be limited when confronted with intricate disease types and extensive datasets. Kulkarni and Ashwin (2012) demonstrated that classifying various plant leaf diseases from images using ANN produced a recognition rate of up to 91%. However, classification relied on features extracted by a Gabor filter from pre-processed images, highlighting textural, chromatic, and other distinctive attributes.

Machine learning techniques require feature extraction for model training, which is time-consuming and dependent on specific conditions. Consequently, researchers have increasingly adopted deep learning approaches. These techniques automatically learn and extract essential features hierarchically at multiple levels (Shoaib et al. 2023), making them more robust than traditional machine learning methods. Deep learning methods perform simple processing in the initial layers, followed by complex feature learning in the upper layers. However, most deep-learning architectures require large datasets for high accuracy (Marcus 2018). Picon et al. (2019) introduced a CNN based on the ResNet50 architecture that effectively integrated supplementary contextual metadata, including crop identification, weather conditions, and geographical location. Their deep learning approach demonstrated the ability to accurately detect and classify 17 different diseases across five crops, achieving an impressive accuracy rate of up to 98%. They also claimed that the proposed model could reduce classifier error by 71%. Chen et al. (2020) introduced a new deep-learning framework, INC-VGGN, for classifying and identifying diseases in rice and maize leaves. They modified the final convolutional layer of VGGNet by incorporating two Inception layers and one global average pooling layer. The Inception layer serves as the primary feature extractor, whereas the global average pooling layer is responsible for classification. Experimental findings indicate that the model performed satisfactorily on both publicly available and self-developed datasets, achieving validation accuracies of 91.83% and 92.00%, respectively.

Hasan et al. (2020) suggested that to effectively use deep classifiers for plant leaf disease detection in hyperspectral data analysis, employing realistic datasets, data augmentation methods, and various pre-trained models is beneficial. This approach enhances accuracy in plant detection and crop management. Conversely, shallow models are considered more suitable for smaller datasets. Their study further revealed that deep learning for automated feature extraction can overcome constraints associated with handcrafted features. Since deep learning (DL) is considerably more advanced than traditional machine learning (ML), it is widely used in plant leaf disease classification. Jackulin and Murugavalli (2022) provided a comprehensive analysis of different pre-trained backbone models used for plant leaf disease detection. They also investigated enhancement techniques and datasets utilized until 2020 and compared machine learning and deep learning techniques in terms of performance and application, highlighting the effectiveness of deep learning models over machine learning models. Liu and Wang (2021) conducted an extensive investigation into the practical implementation of deep-learning models for predicting plant leaf diseases and pests.

The comparison criteria for the different works in this review include CNN architectures (e.g., LeNet, AlexNet, GoogLeNet, DenseNet, VGGNet, ResNet), datasets employed (e.g., PlantVillage, Tomato Diseases Dataset, Wheat Fungi Diseases), and performance metrics (e.g., accuracy, mean average precision (mAP), precision, recall). This review also considers computational complexity, model effectiveness under various environmental conditions, and generalization ability across different plant leaf diseases.

This article provides an overview of current deep learning techniques applied to various datasets for plant leaf disease detection, identifying research gaps. The overarching goal of this review is to understand the effectiveness of CNNs in plant leaf disease detection and classification, addressing questions such as which CNN models are most effective, which datasets are being used, and what key challenges and advancements exist. Limitations of existing research are also reviewed to determine future research directions for developing a reliable deep learning-based plant leaf disease detection system. The key contributions of our work are:

i. A comprehensive systematic literature review investigating various CNN-based techniques for detecting and classifying plant leaf diseases.
ii. An in-depth analysis of the benefits and challenges associated with different CNN models in plant leaf disease detection.
iii. The identification of research gaps and recommendations for future investigations.
iv. A synthesis of existing studies to provide insights into the current state of deep learning applications in plant disease detection.

2 Research methodology

This study explores the existing model, dataset, challenges, and future trends in the field of plant disease detection and classification by reviewing a wide range of literature on the topic. Keywords such as deep learning, convolutional neural networks, plant disease detection, plant disease classification, object detection, and plant disease datasets were used to

Table 1 List of inclusion and exclusion criteria

S/*N*	Articles considered for the study	Articles discarded
1	Articles focused on plant leaf diseases.	Articles not related to plant leaf diseases.
2	Studies using deep learning models.	Short reports or letters.
3	Studies focusing on plant leaf disease datasets.	Articles not written in English.
4	Articles published between 2018 and March 2024.	Articles without full-text availability.

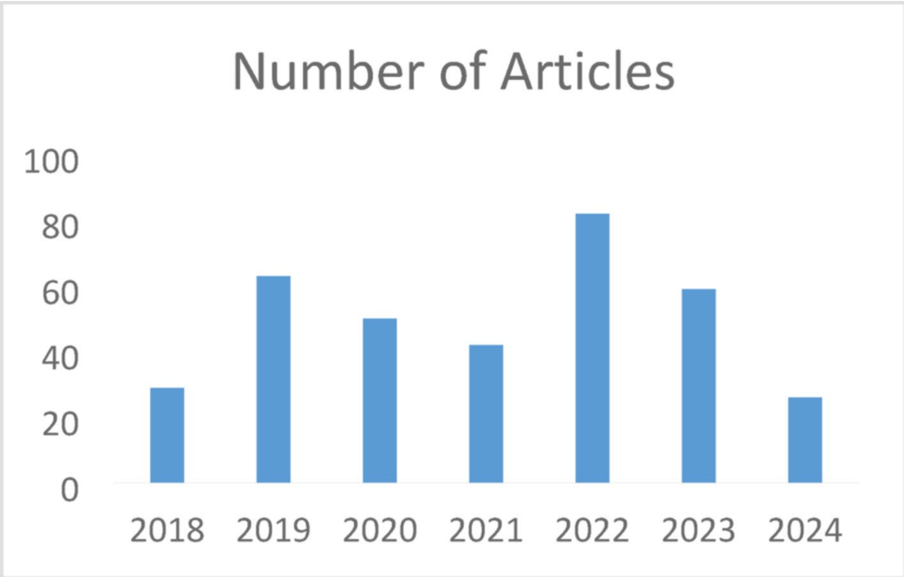


Fig. 1 A pictorial representation of the number of articles published each year

identify relevant survey papers published in well-known journals like IEEE Xplore, Elsevier, Scopus, Springer, ScienceDirect, MDPI, Semantic Scholar, and Google Scholar. After gathering the literature, the author critically examined various techniques and methodologies, analyzed the algorithms, and selected key topics significant to plant leaf disease detection and classification.

2.1 Inclusion/exclusion criteria of articles

The inclusion and exclusion criteria are designed to select research studies relevant to the research questions being investigated. The primary studies were chosen based on the inclusion criteria we have outlined in Table 1. The exclusion criteria were not detailed separately, as they essentially represent the inverse of the specified inclusion criteria. A total of 603 research articles were identified, consisting of journal articles, conference papers, and book chapters, with 78 subsequently removed as duplicates. Figure 1 presents a pictorial representation of the number of articles published between 2018 and 2024.

To ensure that the selected articles were relevant to the use of deep learning (DL) in identifying and classifying plant leaf diseases, the selection procedure looked closely at the titles, abstracts, and entire articles. After careful examination of titles and abstracts, about 426 were discarded based on the selection criteria outlined in Table 1.

2.2 Taxonomy of plant leaf disease detection

To provide a comprehensive understanding of plant leaf disease detection using CNNs, we propose a taxonomy that categorizes the key components of the field, including input data, deep learning techniques, datasets, evaluation metrics, challenges, and applications. This framework guides our review and addresses the research questions outlined below. Input data includes RGB images, multispectral data, and metadata sourced from public datasets like PlantVillage or custom collections. Deep learning techniques encompass segmentation (e.g., FCN, Mask R-CNN), detection (e.g., R-CNN, YOLO), and classification models (e.g., VGG, ResNet). Datasets vary in scope, size, and complexity, while performance is assessed using evaluation metrics such as accuracy and mean average precision (mAP). Key challenges include data limitations, technical complexity, and environmental factors, with applications targeting early detection and crop management. Table 2 summarizes this taxonomy, with details explored in subsequent sections.

2.3 Research questions

To structure the findings of this literature review efficiently, we formulated six research questions that emphasize specific objectives.

- What specific types of data and sources were used?
- What datasets were used in the study?
- What deep learning techniques were employed for classifying plant leaf diseases?
- What are the primary evaluation criteria for assessing the effectiveness of disease detection systems, as well as severity estimation?
- Which classification models have been the most effective?
- What key observations and limitations have been reported by the authors in the study?

3 Geographical distribution of research on plant leaf disease detection using deep learning

To explore the global research landscape on plant leaf disease detection using deep learning, Table 3 highlights the countries and continents where significant studies have been conducted. This table categorizes research based on the types of plant leaf diseases studied and the deep learning models used for detection. Plant leaf diseases pose a major threat to global food security, impacting crop yields across various regions. Their prevalence and severity depend on factors such as climate, agricultural practices, and disease management strategies. Analyzing the geographical distribution of plant leaf diseases and related research efforts helps identify key outbreaks, assess their impact on agricultural production, and evaluate the application of deep learning models in addressing these challenges.

Table 2 Taxonomy of plant leaf disease detection using CNNs

Category	Subcategory	Description
Input Data	RGB Images	Standard colour images of leaves showing visible disease symptoms.
	Multispectral/Hyperspectral	Multi-wavelength images for early detection, often from drones or cameras.
	Contextual Metadata	Supplementary data (e.g., weather, crop type) enhancing model accuracy.
Deep Learning Techniques	Segmentation Networks	
	- Fully Convolutional Networks (FCN)	Pixel-level classification of disease regions.
	- Mask R-CNN	Instance segmentation for precise lesion isolation.
	Detection Methods	
	- Two-Stage (R-CNN, SPP-Net)	Region proposal followed by classification, high accuracy but slower.
	- One-Stage (YOLO, SSD)	Direct prediction, fast but less precise for small targets.
	Classification Models	
	- VGG	High accuracy, computationally intensive.
	- ResNet	Robust with residual learning, top performer.
	- EfficientNet	Lightweight, efficient for resource-limited settings.
Datasets	Scope	
	- Single-Plant	Focused on one crop species.
	- Multi-Plant	Covers multiple species.
	Complexity	
	- Controlled Background	Simple settings, easier detection.
	- Natural Settings	Real-world complexity is challenging for models.
	Size	
	- Small	Limited images, constrains training.
	- Large	Extensive images, supports robust models.
4. Evaluation Metrics	Accuracy	Overall correctness of classification/detection.
	mAP	Mean Average Precision for detection performance.
	Precision/Recall	Balance of true positives vs. missed/falsely detected cases.
	Speed (FPS)	Frames per second for real-time capability.
5. Challenges	Data-Related	Small datasets, complex backgrounds limit performance.
	Technical	High computational cost, small lesion detection issues.
	Environmental	Lighting, occlusion, weather affect image quality.
6. Applications	Early Detection	Identifying diseases before visible symptoms escalate.
	Severity Estimation	Quantifying disease extent for management.
	Crop Management	Guiding farmer decisions with actionable insights.

Table 3 Geographical distribution of research on plant disease detection using deep learning

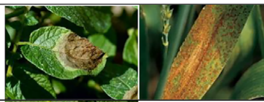
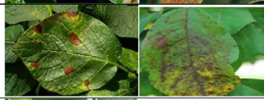
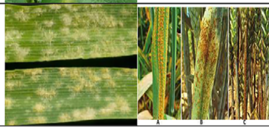
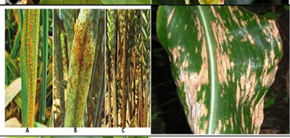
Continent	Country	Diseases Studied	Pictorial Representation	Key Studies & Models Used
North America	United States	Late blight (Tomato), Rust (Wheat)		EfficientNet (Atila et al., 2021), YOLOv4 (Bochkovskiy et al., 2020)
	Canada	Potato blight, Apple scab		AlexNet, GoogleNet, VGG and R-CNN (Arshaghi et al., 2023), CNN (Lafi & Abu-Naser, 2024)
Europe	United Kingdom	Grapevine mildew, Leaf spot		DeiT, MaxViT, and MobileViT (Muthu et al., 2024)
	Germany	Powdery mildew (Barley), Rust (Wheat)		SVM and KNN (Muthu et al., 2024) ResNet50 (M. Long et al., 2023)
	Spain	Olive tree diseases		Inception V3 (Anwar et al., 2023), Mast-R CNN Inception v2 (Bocca et al., 2023)
Asia	China	Rice blast, Maize leaf blight		YOLOv3 (Liu & Wang, 2020), EfficientNet (Liu et al., 2020)
	India	Banana wilt, Tomato leaf curl		KNN, SVM and Alexnet (Vidhya & Priya, 2022), CNN (Trivedi et al., 2021)

Table 3 (continued)

	Japan	Citrus canker, Rice blast		GoogLeNet (Wu et al., 2020), MobileNetV2 (da Silva et al., 2023), CNN (Gogoi et al., 2023)
Africa	South Africa	Maize streak virus, Cassava mosaic		VGG (Simonyan & Zisserman, 2015)
	Kenya	Coffee leaf rust, Tea blight		YOLOv3 (Bhatt et al., 2019)
South America	Brazil	Soybean rust, Coffee leaf rust		Faster R-CNN (Fuentes et al., 2017)
	Argentina	Wheat rust, Maize leaf blight		ResNet (He et al., 2016)
Australia	Australia	Grapevine downy mildew, Wheat rust		VGG (Simonyan & Zisserman, 2015)

4 Plant leaf disease datasets

Studies on plant leaf disease detection often rely on self-developed datasets due to the limited availability of suitable public datasets. However, several publicly available datasets exist, including the PlantVillage dataset (Hughes and Salathe 2015), the New Plant Disease dataset, the DiaMOS dataset (Parraga-Alava et al. 2019), the Tomato Diseases dataset, the Grape Disease Dataset, the Citrus Dataset (Rauf et al. 2019), the Soybean Diseases Dataset (De Galiza Barbosa et al. 2022), the RoCoLe Dataset (Parraga-Alava et al. 2019), the BRACOL Dataset (Esgario et al. 2020), the Rice Leaf Disease dataset (Prajapati et al. 2017), the Cassava Disease dataset (Mwebaze et al. 2019), the CD&S (Corn Disease & Severity) dataset (Aanis et al. 2021), and the PlantDoc dataset (Singh et al. 2020). Many studies referenced in this review utilize these datasets for CNN-based plant leaf disease detection, which will be analyzed and discussed. Figures 2 and 3 illustrate sample plant leaf images from datasets such as PlantVillage, Soybean Disease Leaf, and Citrus Datasets. These images feature various plant diseases, including Potato early blight, Potato late blight, Pepper bacterial spot, Strawberry scorch, Tomato early blight, Soybean septoria, Citrus greening, and Citrus canker. Among these datasets, PlantVillage has been widely used for plant disease detection and classification (Falaschetti et al. 2022; Gui et al. 2021). It contains 54,305 single-leaf images covering 17 fungal diseases, 4 bacterial diseases, 2 mold diseases, 2 viral diseases, and 1 mite-induced disease across 14 crop species. The images were captured on sunny or

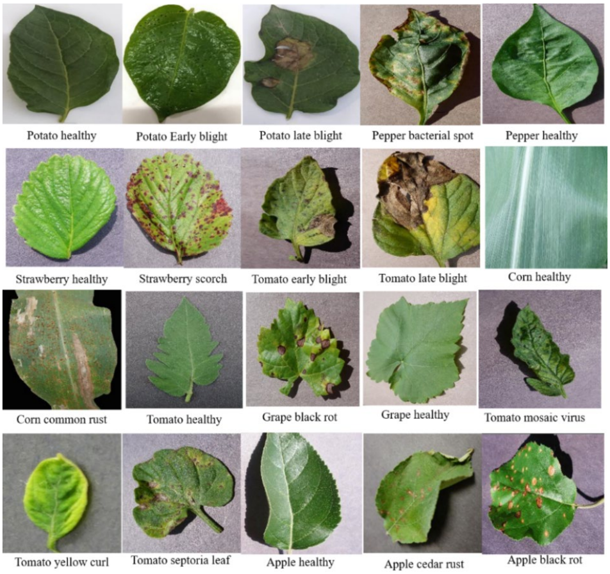


Fig. 2 Sample plant leaf images depicting various diseases from the PlantVillage dataset (Hughes and Salathe 2015).

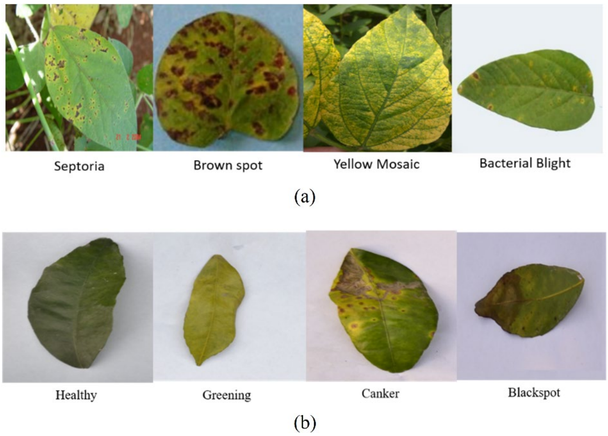


Fig. 3 Examples of plant leaf images depicting various diseases from (a) the Soybean disease leaf dataset (De Galiza Barbosa et al. 2022) and (b) the Citrus dataset (Rauf et al. 2019).

cloudy days with gray or black backgrounds using Canon EOS 1100D, EOS 600D, and EOS 60D cameras. However, its primary limitation is the lack of images with complex backgrounds, making it less challenging for deep-learning models (Hughes and Salathe 2015).

The PlantDoc dataset comprises 2,598 multi-leaf images collected from online sources such as Google Images and Ecosia (Singh et al. 2020). It includes 17 disease classes across 13 plant species, such as apple, bell pepper, corn, grape, potato, soybean, and tomato. However, limited domain expertise may have led to some misclassifications within the dataset. The DiaMOS Plant dataset (Fenu and Malloci 2021) captures the complete growth cycle of a pear tree from February to July, offering a comprehensive sample of key cultural elements. It consists of 3,505 images, including 499 fruit images and 3,006 leaf images, covering four disease types at four severity levels and four fruit growth stages. Images were taken with a smartphone (Honor 6X) and a DSLR (Canon EOS 60D), resulting in resolutions of 2976

×3968 and 3456 ×5184 pixels. The dataset is well-suited for machine learning and deep learning applications in classification and detection tasks. The Robusta Coffee Leaf Image Dataset (RoCoLe) includes 1,560 leaf images categorized into six classes: healthy, red spider mite presence, and rust at four progressive stages (Parraga-Alava et al. 2019). Captured in uncontrolled environments with a smartphone, images were captured at distances of 200 mm and 300 mm on both the adaxial (upper) and abaxial (lower) leaf surfaces. The dataset also provides segmentation annotations created using the Labelbox web tool. The BRACOL dataset (Esgario et al. 2020) contains 1,747 images of Arabica coffee leaves affected by various biotic stresses, including leaf miner infestation, rust, brown leaf spot, and Cercospora leaf spot. Captured in Espirito Santo, Brazil, images were taken with five smartphones under semi-controlled conditions. Labeling was conducted in the presence of an expert to ensure accuracy.

The Citrus dataset (Rauf et al. 2019) includes 759 images of citrus fruits and leaves, classified as healthy or affected by diseases such as black spots, canker, greening, scab, and melanosis. A DSLR camera was used to capture images under expert supervision. The dataset is valuable for applying advanced computer vision techniques to plant disease detection. The Rice Leaf Disease dataset (Prajapati et al. 2017) consists of 120 rice leaf images captured using a Nikon D90 DSLR camera (12.3 MP) with a resolution of 2848 ×2848 pixels. Collected in Shertha, India, against a white background, the dataset is limited in size and variety. The Tomato Diseases Dataset (Bayram and Alatas 2022; Thuseethan et al. 2022) comprises 19,510 images of tomato leaves affected by 10 different diseases, including early blight, late blight, and yellow leaf curl virus. The images were taken with a mobile camera at 1024 × 1536 pixels, focusing on a single plant species. The APDA dataset (Akhtar et al. 2013) consists of 40 images provided by the Tea Research Institute in Mansehra, categorized into healthy and diseased leaves. It covers two tea plant diseases—anthracnose and black spots. Captured using a Nikon D90 camera under controlled lighting at a fixed distance of 9–12 inches, the dataset is significantly limited in size.

While the datasets above represent key resources for CNN-based detection, Sunil et al. (2023) document approximately 50 datasets, offering a broader perspective on the field's resources. These include recent additions like the Cassava Leaf Disease Dataset (Mwebaze et al. 2019), the Apple Leaf Disease Dataset (Kaggle), and the Maize Disease Dataset (Wiesner-Hanks et al. 2018), alongside specialized datasets for pests (e.g., the Coffee Leaf Disease Dataset, Lisboa et al. 2022) and severity estimation (e.g., the DiaMOS Plant dataset). This progression from small, controlled datasets (e.g., APDA, 40 images) to large, field-based collections reflects an evolution toward practical, real-world detection, supporting advanced CNN models and farmer decision-making.

A Cardamom Plant dataset has been published for CNN-based disease detection, comprising 1,724 leaf images of Elettaria cardamomum (Sunil et al. 2022). Developed by Sunil Chinnahalli and utilized with an EfficientNetV2 model, this dataset supports binary and multi-class classification of cardamom diseases, reflecting the growing availability of crop-specific, field-collected data for deep learning applications. Available upon request, it complements broader datasets by focusing on a high-value spice crop prone to diseases such as leaf blight and capsule rot.

Table 4 summarizes these datasets, detailing their scope, plant varieties, and research applications. This information is crucial for researchers aiming to evaluate or compare their models using established benchmarks.

Table 4 Existing datasets and their respective features

Dataset Name	Description	Plant covered	Research
PlantVillage Dataset (Hughes and Salathe 2015)	Contains about 54,000 single-leaf images of 17 fungal diseases, 4 bacterial diseases, 2 mold diseases, 2 viral diseases, and 1 disease caused by a mite from 14 crop species.	Multiple crops: Apple, Blueberry, cherry, corn, grape, orange, peach, pepper bell, potato, raspberry, soybean, squash, strawberry and tomato	(Akhtar et al. 2013)-(Atila et al. 2021b; Aldakheel et al. 2024) (Khan et al. 2023) (Li et al. 2023a, b) (Falaschetti et al. 2022)
Tomato Diseases Dataset	Comprises of 19,510 images of tomato leaves affected by 10 different diseases.	Tomato	(Bayram and Alatas 2022)-(Thuseethan et al. 2022) (Astani et al. 2022)
Wheat Fungi Diseases (Genaev et al. 2021)	Contains 2,414 images of wheat plant species affected by 5 different fungal diseases, which include powdery mildew, stem rust, leaf rust, septoria, and yellow rust.	Wheat	(Elizar et al. 2022; Rößle et al. 2023)
Grape Disease Dataset	Contains 1,680 images of grape leaves affected by 4 class diseases, which are powdery mildew and black rot.	Grape	(Rossi et al. 2022); Fraiwan et al. 2022)
Citrus Dataset (Rauf et al. 2019)	It contains 759 of both healthy and infected images of which 609 are citrus leaves and 150 citrus fruits. Infected by 4 diseases, including citrus canker, black spot, melanoses, and greening.	Citrus	(Palei et al. 2023)-(Barman and Choudhury 2022); Zhang et al. 2022); Çetiner 2022)
Soybean Diseases Dataset (*Soybean Diseased Leaf Dataset*, n.d.)	There are a total of 6,410 pictures, containing healthy plants, caterpillar-damaged plants, and diabrotica speciosa.	Soybean	Nil
Apple Diseases Dataset (*Apple Leaf Diseases*, n.d.)	Consists of 9,714 images of apple leaves with four disease categories.	Apple	(L. Li et al. 2022a, b)
Northern Leaf Blight (NLB) (Wiesner-Hanks et al. 2018)	Consists of 18,222 images of corn plants affected by NLB captured from a field environment.	Maize	(Ahmad et al. 2023)
Plant Pathology Challenge Dataset	This dataset consists of over 18,000 images of apples, blueberries, grapes, and strawberries, both healthy and unhealthy plants.	Multiple crops: apple, blueberry, grape, and strawberry	(Yadav et al. 2022)
DiaMOS plant Dataset (Parraga-Alava et al. 2019)	It is a collection of 3505 pear leaf images of both healthy and diseased leaves. Images were gathered using different devices including a smartphone (Honor 6×) and a DSRL camera (Canon EOS 60D). Image categories: leaf spot, leaf curl, slug damage, and healthy leaf	Pear	(Parraga-Alava et al. 2019) (Malloci 2021)

Table 4 (continued)

Dataset Name	Description	Plant covered	Research
RoCoLe Dataset (Parraga-Alava et al. 2019)	Contains 1,560 leaf images divided into six classes: healthy, red spider mite presence, rust level 1, rust level 2, rust level 3, and rust level 4. The images were captured from the adaxial (upper) and abaxial (lower) leaf sides, under a natural uncontrolled environment.	Coffee	(Parraga-Alava et al. 2019)
BRACOL Dataset (Esgario et al. 2020)	Comprised 1,747 images of arabica coffee leaves with various diseases such as leaf miner, leaf rust, brown leaf spot, and Cercospora leaf spot. All images were obtained using various mobile devices (ASUS Zenfone 2, Xiaomi Redmi 5 A, Xiaomi S2, Galaxy S8, and iPhone 6 S)	Coffee	(Fenu and Malloci 2022); Bordin Yamashita and Leite 2023); Lisboa et al. 2022)
Rice Leaf disease (Prajapati et al. 2017)	Consists of 3,545 images of rice leaves, with 779 images of leaf blasts, 523 images of brown spots, 565 images of Hispa, and 1,488 images of healthy leaves. The images were captured using a smartphone camera in natural light conditions, and the resolution of the images is 1,024 × 1,024 pixels.	Rice	(Prajapati et al. 2017); Yu et al. 2022)-(Sharma et al. 2021)
APDA Dataset (Akhtar et al. 2013)	Comprises 40 images, categorized into two groups: healthy images and unhealthy images namely anthracnose and black spots.	Rose	(Arsenovic et al. 2019; Karthik et al. 2020)
Cassava Disease dataset (Mwebaze et al. 2019)	Consists of a total of 9,430 labeled images. The images were divided into three sets, a training set (5,656), a testing set (1885), and a validation set (1889).	Cassava	(Oyewola et al. 2021)
CD&S (Corn Disease & Severity) (Aanis et al. 2021)	It consists of 4,455 images of corn leaves, with three different classes of corn diseases, namely gray lead spot (1905), northern leaf spot (1313), and northern leaf blight (1237).	Corn	(Ahmad et al. 2023)
PlantDoc dataset (Singh et al. 2020)	PlantDoc contains 2598 multi-leaf images collected from the internet, downloaded from Google Images and Ecosia. It comprises 13 plant species which include apple, bell pepper, blueberry, cherry, corn, grape, peach, potato, raspberry, soya bean, squash, strawberry, and tomato	Multiple crops: apple, bell pepper, blueberry, cherry, corn, grape, peach, potato, raspberry, soya bean, squash, strawberry, and tomato	(Hasan et al. 2020)
Cardamom Plant Dataset (Sunil et al. 2022)	1,724 leaf images for disease detection	Cardamom (Elettaria cardamomum)	(Sunil et al. 2022)
Sugarcane leaf dataset (Thite et al. 2024)	The dataset comprises 6,748 high-resolution leaf images categorized into nine disease types, along with healthy and dried leaf classes. It includes diseases such as smut, yellow leaf disease, pokkah boeng, mosale, grassy shoot, brown spot, brown rust, banded chlorosis, and sett rot.	Sugarcane leaf	(İshak and İsmail 2024)

5 Image-capturing techniques, challenges, and solutions

Accurate disease detection relies on high-quality image data. Various image-capturing techniques are used, each presenting unique challenges and solutions:

i. *Smartphone Cameras*: Smartphones are widely used for their portability, affordability, and ease of use, allowing farmers and researchers to document plant diseases in the field (Chen et al. 2020). However, low resolution in poor lighting, background noise from surrounding elements, and inconsistencies in angles and distances can reduce accuracy (Barbedo 2018). Solutions include using high-resolution cameras with advanced sensors, applying preprocessing techniques (e.g., background removal, normalization), and standardizing capture protocols for consistent imaging (Liu and Wang 2021).
ii. *Drones (UAVs)*: Drones equipped with high-resolution or multispectral sensors enable large-scale disease monitoring (Liu et al. 2021). However, their effectiveness is affected by weather conditions, high costs, and the need for substantial data storage and processing (Zhang et al. 2019). Improvements include weather-resistant drones with stabilization, cost-effective models for broader accessibility, and edge computing to process data directly on the drone, reducing transmission and storage demands (Kouadio et al. 2023).
iii. *Multispectral & Hyperspectral Imaging*: These technologies capture images across multiple wavelengths, enabling early disease detection beyond the visible spectrum. However, challenges include high costs, specialized training requirements, and complex data processing (Kerkech et al. 2020). Solutions involve developing cost-effective agricultural multispectral cameras, leveraging cloud-based platforms for processing, and training programs to improve usability for researchers and farmers.

6 Deep learning-based segmentation network

A segmentation network is a computational method for partitioning an image into distinct segments or regions with similar characteristics or belonging to the same class. The clustering process involves using predetermined criteria, such as color, size, or texture, to group similar elements together (Shoaib et al. 2023). This approach involves converting the task of identifying plant leaf diseases into a process of semantic and instance segmentation. Applying a segmentation network to images has proven effective in detecting and classifying plant leaf diseases. The classification approaches can be categorized into two approaches: Fully Convolutional Networks (FCN) (Long and Shelhamer 2015) and Mask R-CNN (Liu and Wang 2021).

6.1 Fully convolutional networks (FCN)

Fully Convolutional Networks serve as the fundamental framework for image semantic segmentation. Most semantic segmentation models rely on Fully Convolutional Networks (FCN). An FCN first performs feature extraction and encoding on the input image through convolution. It then restores the feature image to the dimensions of the input image using deconvolution or up-sampling techniques. The FCN methods commonly used for plant leaf disease detection include conventional FCN, U-Net (Weng and Zhu 2021), and SegNet (Badrinarayanan et al. 2017), in which each differs in the FCN network structure. Figure 4 shows the FCN framework, for instance, segmentation. Kerkech et al. (2020) applied FCNs to detect vineyard mildew in images captured by Unmanned Aerial Vehicles (UAVs). Their approach integrated visible and infrared images from two sensors, using a novel image registration technique for precise alignment. A fully convolutional network then classified pixels such as shadow, ground, healthy, or symptomatic. The method achieved an 89% detection rate at the vine level and 84% at the leaf level, demonstrating its effectiveness for vineyard disease monitoring.

Wang and Zhang (2018) developed an FCN-based technique for segmenting maize leaf diseases. The process involved preprocessing, enhancing image data, and generating deep-learning datasets. The FCN produced feature maps, which were then upsampled and deconvolved. The method achieved an accuracy rate exceeding 96%, demonstrating its effectiveness. The experiment utilized a self-acquired dataset of 750 images captured under normal lighting conditions. Lin et al. (2019) employed a U-Net CNN to segment 50 cucumber powdery mildew leaves. By incorporating a batch normalization layer, the model achieved an average pixel accuracy of 96.08%, surpassing other segmentation methods such as K-means, Random Forest, and Gradient Boosting Decision Tree (GBDT). The U-Net method proved effective in isolating lesion areas within complex backgrounds while maintaining high accuracy and processing speed, even with a limited dataset.

6.2 Mask RCNN

Mask R-CNN is widely recognized as an effective technique for image instance segmentation. This approach functions as a multitask learning method, utilizing a network architecture for both detection and segmentation (Liu and Wang 2021). Instance segmentation with Mask R-CNN allows for the precise separation of individual lesions, enabling accurate quantification of lesion numbers. This is particularly beneficial when multiple lesions of the same type are closely clustered or overlapping. In contrast, semantic segmentation often merges multiple lesions of the same category into a single entity. Figure 5 illustrates the Mask R-CNN structure.

A study by Stewart et al. (2019) employed a Mask R-CNN model to accurately segment lesions caused by maize northern leaf blight (NLB) in images captured by an uncrewed aer-

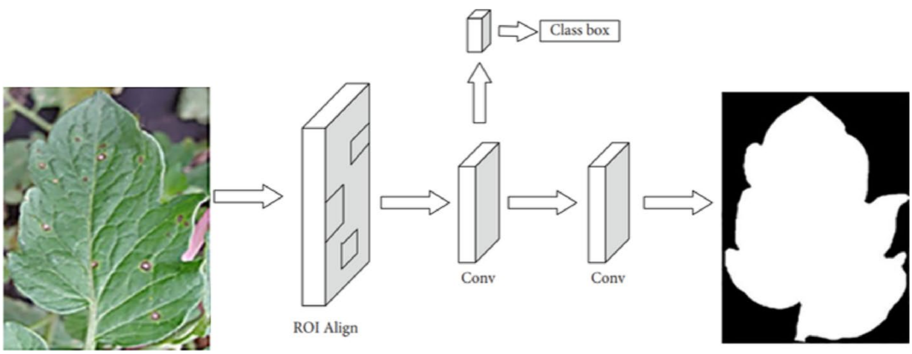


Fig. 4 The FCN framework for instance segmentation (Wang et al. 2019)

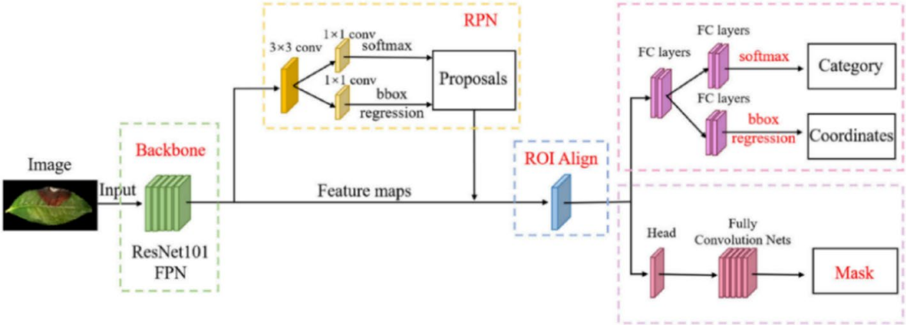


Fig. 5 The structure of the Mask R-CNN (Li et al. 2022a, b)

ial vehicle. The model demonstrated high accuracy in detecting and segmenting individual lesions. At an Intersection over Union (IoU) threshold of 0.50, the IoU between the baseline true value and the predicted lesion was 0.73, while the average accuracy was 0.96. Several studies have integrated Mask R-CNN with object detection networks to enhance plant leaf disease identification and classification. For example, Wang et al. (2019) utilized the Faster R-CNN model to classify tomato diseases and incorporated Mask R-CNN to accurately detect and segment infected regions. Their dataset, sourced from online platforms, was divided into training, validation, and testing subsets. The results showed that the model effectively detected 11 distinct tomato diseases with high accuracy. Additionally, it successfully mapped the spatial distribution and morphological characteristics of infected regions, achieving an impressive 99.64% detection rate across all disease categories. Table 5 summarizes key studies on deep learning-based segmentation networks.

In summary, both FCN and R-CNN represent powerful yet distinct deep learning approaches for image segmentation and object detection. FNCs are well-suited for semantic segmentation, where each pixel in an image is assigned a label. This makes FCNs effective for detailed lesion segmentation in plant leaves. However, they may struggle to distinguish closely spaced objects due to their reliance on a broader image context. Region-based Convolutional Neural Networks (R-CNN), particularly Mask R-CNN, excel in instance segmentation, allowing precise identification and separation of individual lesions. This makes them highly effective for disease quantification and localization, though they tend to be computationally intensive and slower than FCNs.The choice between these methods depends on the specific requirements of the task, including precision, speed, and available computational resources for plant leaf disease detection.

7 Deep learning-based detection methods

Object detection is a fundamental task in computer vision, aiming to determine both the precise location and category of an object. Currently, deep learning-based methods for plant leaf disease detection are continuously evolving. These methods are generally categorized into one-stage and two-stage networks (Du et al. 2020). The main difference is that two-stage networks first generate candidate boxes to identify potential lesions before performing detection. In contrast, a one-stage network makes predictions directly using features

Table 5 Summary of research on the deep learning-based segmentation network

References	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Kerkech et al. 2020)	Vineyard mildew	Self-acquired	FCN	84%	The FCN model successfully integrated visible and infrared images, providing an 84% detection accuracy at the vine level and demonstrating its potential for vineyard disease detection	Struggled with precision in separating symptomatic and non-symptomatic areas under more complex conditions.
(Z. Wang and Zhang 2018)	Maize leaf	Self-acquired (750 images)	FCN	96.80%	The FCN model yielded high accuracy (96.8%) in segmenting maize leaf diseases under normal lighting conditions, proving the model's robustness for agricultural datasets.	Limited generalizability due to the controlled dataset; may not perform as well in varied environmental conditions.
(Lin et al. 2019)	Cucumber	Self-acquired (50 images)	U-net	96.08%	The U-net model was highly effective in segmenting cucumber powdery mildew lesions, achieving 96.08% accuracy with complex backgrounds, outperforming K-means and other models.	Model performance was tested on a small dataset (50 images), which may not generalize to larger or more diverse datasets.

Table 5 (continued)

References	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Stewart et al. 2019)	Maize	Self-acquired (7669 UAV-based images)	Mask R-CNN	96%	Mask R-CNN demonstrated high accuracy (96%) in segmenting lesions from UAV-based images, with superior performance in distinguishing individual lesions.	Computationally intensive and slower due to its multitasking nature, making it less suitable for real-time applications.
(Wang et al. 2019)	Tomato	İnternet (286 images)	Faster R-CNN and Mask R-CNN	99.64%	The combination of Faster R-CNN and Mask R-CNN resulted in a notable detection rate (99.64%) for tomato diseases, efficiently identifying the spatial distribution of infected regions.	High computational requirements limit its usability in low-resource settings.

extracted from the network. Figure 6 illustrates the categories of the deep learning-based detection method.

7.1 Two-stage network-based detection methods

A two-stage network for object detection typically consists of multiple interconnected modules, each responsible for specific tasks, as illustrated in Fig. 7. Although these networks are more complex and exhibit slower detection speeds, they offer higher accuracy. In the first stage, regions of interest (ROIs) are generated, while the second stage performs regional classification and refines the ROI locations identified in the initial stage (Du et al. 2020). Commonly used two-stage models include R-CNN (Region-based Convolutional Neural Network) and SPP-Net, which are further discussed in the following subsections.

7.1.1 R-CNN (region-based CNN)

Girshick et al. (2014) introduced the R-CNN framework, which utilizes a selective search algorithm for object detection, as illustrated in Fig. 8. The proposed architecture generates approximately 2,000 region proposals to compute CNN features. Additionally, a Support Vector Machine (SVM) model is employed to classify the extracted features within the region proposals. To improve the accuracy of object localization, a bounding box regressor is implemented. Dalai and Senapati (2019) proposed an automated pest detection framework

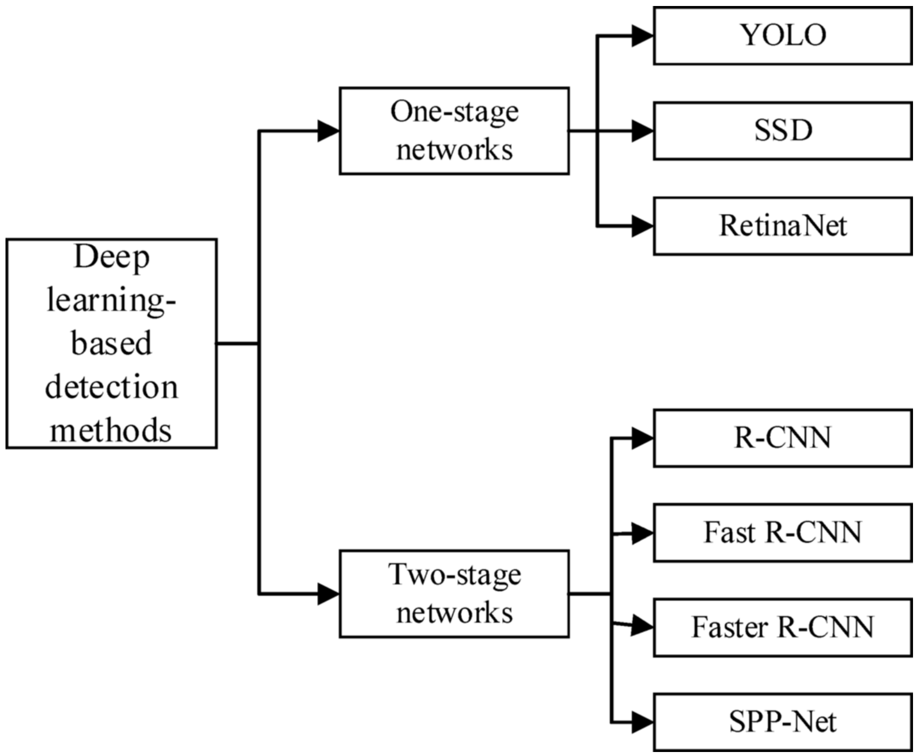


Fig. 6 Commonly used Deep learning-based detection methods

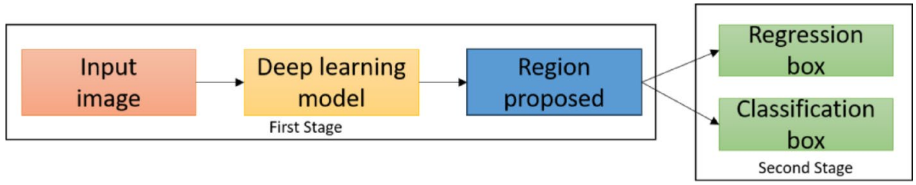


Fig. 7 Two-stage approach (Nurkarim and Wijayanto 2023)

using R-CNN, demonstrating a notable improvement in detection accuracy. Their approach employs a stream path-based R-CNN architecture, where features extracted from a CNN are processed by Region Proposal Networks (RPNs) for object detection, specifically targeting ocean eddies. Despite its advancements in object detection, R-CNN has several limitations, including slow processing speed, a multi-stage training pipeline, and the inflexibility of the selective search method.

To address these issues, Girshick (2015) introduced Fast R-CNN, an enhanced version of R-CNN and SPPNet. The Fast R-CNN network takes an image and a set of object proposals as input. It utilizes convolutional and max pooling layers to generate a convolutional feature map. A Region of Interest (RoI) pooling layer then extracts a fixed-length feature vector from the feature map for each object proposal. This feature vector is passed through a series

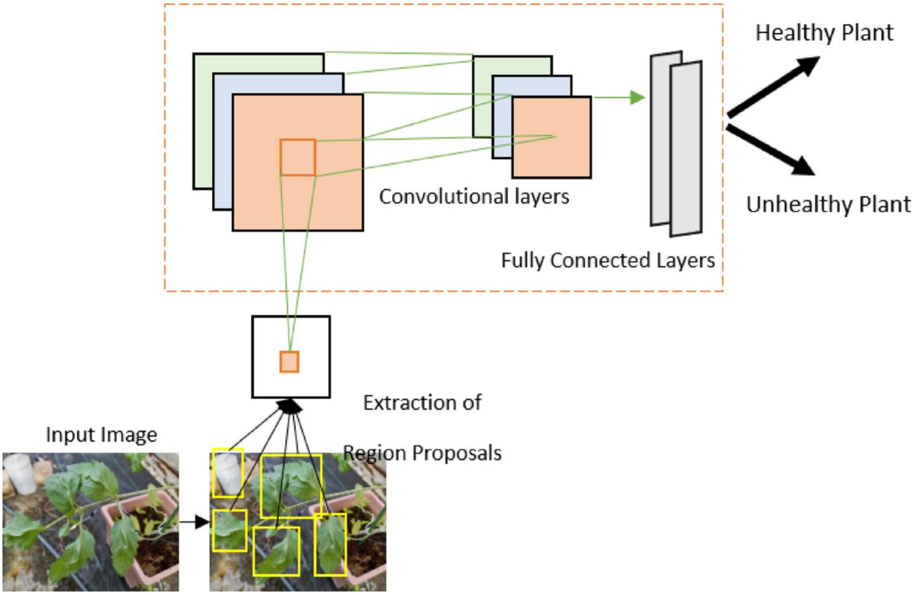


Fig. 8 Basic Block Diagram of RCNN (Kesav and Jibukumar 2022)

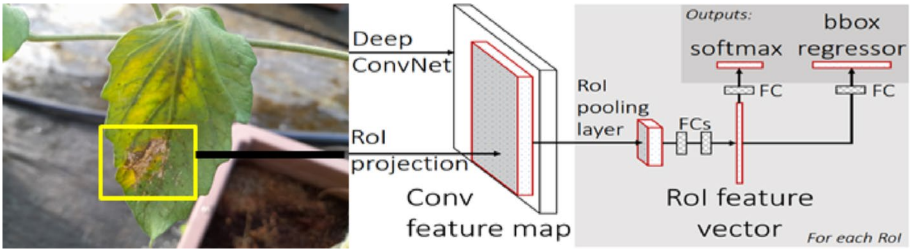


Fig. 9 Network structure diagram of Faster R-CNN (Girshick 2015)

of fully connected (FC) layers, which split into two separate output layers. The first output layer generates softmax probability estimates for K object classes, including a "background" class, while the second output layer produces four real-valued numbers representing precise bounding box coordinates for each object class. However, Fast R-CNN still relies on the selective search method, which is computationally expensive and time-consuming. Faster R-CNN addresses these limitations by replacing selective search with a Region Proposal Network (RPN). The feature extractor first obtains a feature map from the input image. The RPN then calculates anchor box confidences and generates region proposals. The feature maps of the proposed regions are passed through the RoI pooling layer, refining the initial detection results and determining the location and type of lesions. Figure 9 illustrates the basic network structure of Faster R-CNN. This method improves traditional structures by modifying feature extractors, anchor ratios, RoI pooling, and loss functions. These modifications make Faster R-CNN better suited for plant leaf disease detection.

Faster R-CNN was first successfully applied to detect plant diseases and pests in a dataset of 4,800 images across 11 categories, as demonstrated by Fuentes et al. (2017). The model achieved a mean average precision (mAP) of 88.66%. Li et al. introduced Strawberry R-CNN, a modified Faster R-CNN model, to detect and count strawberries in natural environmental settings. Their model achieved an average precision of 0.9019, an mAP of 0.8447, and a counting accuracy of 99.1%. Similarly, Wang et al. (Wang et al. 2023) developed a modified Faster R-CNN architecture to detect sweet potato leaves collected from the field. Their approach achieved an impressive mAP of 95.7%.

Ozguven and Adem (2019) used Faster R-CNN to detect Cercospora beticola Sacc., a leaf spot disease in sugar beet leaves. The model was trained and evaluated on 155 images, achieving a classification accuracy of 95.48% despite the limited dataset size. Xie et al. (2020) introduced the Faster DR-IACNN model for detecting grape leaf diseases. This approach was tested using a self-developed Grape Leaf Disease Dataset (GLDD) and builds upon the Faster R-CNN detection algorithm. To enhance feature extraction, the model incorporates the Inception-v1 module, Inception-ResNet-v2 module, and SE-blocks. Experimental results indicate that Faster DR-IACNN achieved a mean average precision (mAP) of 81.1% on GLDD, with a detection speed of 15.01 FPS. Ghoury et al. (2019) employed Faster R-CNN, Inception v2, and SSD MobileNet architectures to detect grape leaf diseases. Their results showed that Faster R-CNN Inception v2 achieved significantly higher classification accuracy than SSD, ranging from 78 to 99% across test images. However, Faster R-CNN required more processing time, while SSD MobileNet V1 performed better in cases with minimal noise and uniform backgrounds, achieving 90–99% accuracy. The SSD model, however, struggled to detect small objects effectively.

Gené-Mola et al. (2019) utilized Faster R-CNN to identify tall spindle 'Fuji' apples in nighttime images captured under artificial lighting. Their model detected 12,839 fruits across 967 images, achieving an average precision (AP) of 0.948. Similarly, Liu et al. (2019) applied a Faster R-CNN-based VGG16 model to identify apple images with few fruits under natural lighting, achieving an F1-score of 90.57%. Wan and Goudos (2019) also improved Faster R-CNN performance, attaining an AP of 0.925 on 820 images. Zhang et al. (2021) introduced a multiple-feature fusion-based soybean leaf disease detection system using Faster R-CNN. Their MF3 R-CNN model, trained exclusively on a synthetic dataset, demonstrated high efficacy in detecting soybean leaf diseases in complex environments, achieving an optimal mAP of 83.34%. Faster R-CNN has consistently demonstrated high accuracy in plant disease detection. Bansal et al. (2023) developed a hybrid model combining Faster R-CNN and SVM to detect and classify wheat leaf spot disease, achieving an accuracy of 96.63%. Similarly, Rajasree et al. (2023) applied Faster R-CNN to identify cassava brown streak virus disease using 1,000 images from Kaggle's public dataset, achieving an accuracy of 96%.

7.1.2 Spatial pyramid pooling networks (SPP-Net)

He et al. (2014) introduced Spatial Pyramid Pooling Networks (SPP-Net), enabling a CNN to generate fixed-length representations for regions of interest without requiring image rescaling. This model allows feature maps to be computed from the entire image once, after which fixed-length representations can be extracted for arbitrary sections to train object detectors. SPP-Net significantly improves detection speed compared to the R-CNN model while maintaining detection accuracy, as demonstrated by its VOC07 mean average precision (mAP) score of 59.2%. However, despite these advancements, SPP-Net has certain limitations. The training process remains multi-stage, which can introduce inefficiencies and complexity. Additionally, SPP-Net only fine-tunes its fully connected layers, overlooking the potential benefits of optimizing earlier layers in the network. Figure 10 illustrates the network structure of SPP-Net.

Ma et al. (2023) introduced an enhanced SPP-Net to detect crop diseases in visually complex environments. The approach integrates a dual-attention module into the CSPNet backbone network, enabling the extraction of disease-related features across multiple dimensions, specifically from channel and spatial perspectives. SPP-Net was employed to expand the receptive field, reduce model fitting time, accelerate network convergence, and enhance disease detection efficiency. The study utilized a dataset of 6,568 field-acquired images of both healthy and diseased crops, achieving a mean average precision (mAP) of 90.15%. Abdani and Zulkifley (2019) proposed a method that combines SPP-Net with an improved DenseNet architecture for plantation detection at varying scales. SPP-Net's multi-scale feature extraction capability enabled the effective identification of oil palm plants. Using 15,262 images from the WiDS Kaggle competition, their approach achieved an accuracy of 99.08%. Yuan et al. (2021) introduced a spatial pyramid-oriented encoder-decoder convolutional neural network (SPEDCCNN) based on SPP-Net and CNN for disease identification and segmentation. The model was tested on a dataset of 125 field-acquired images of maize, wheat, and cucumber, covering six distinct disease classifications, and demonstrated an accuracy exceeding 90%.

In conclusion, R-CNN and SPP-Net are categorized as two-stage detection methods because they first generate region proposals and then classify their contents. When applied to plant leaf disease detection, these networks enable precise localization and classification of diseases, making them highly valuable for agricultural applications and crop monitoring.

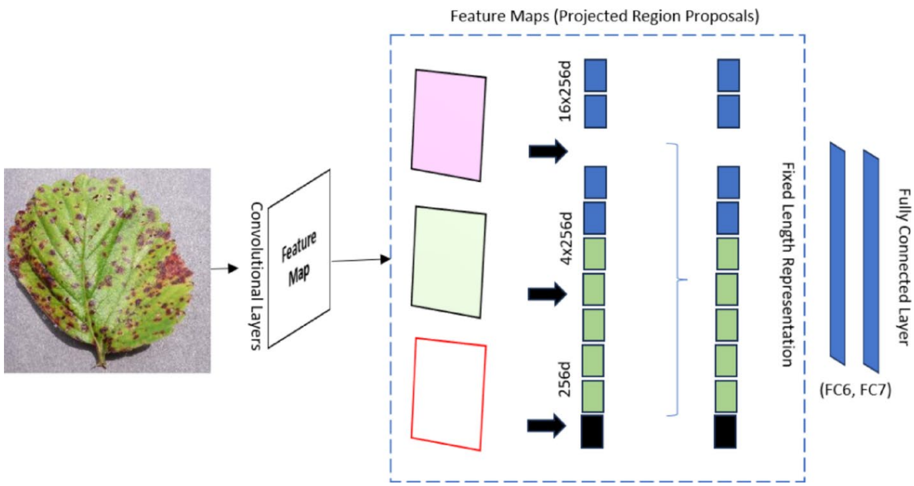


Fig. 10 The architecture of SPP-net for object detection (Aziz et al. 2020)

7.2 One-stage network-based detection methods

A one-stage network performs classification and regression simultaneously, employing regular and dense sampling techniques to capture information about locations, scales, and aspect ratios. Consequently, inference speed is significantly improved compared to two-stage detection networks. Examples of one-stage detection networks are SSD, YOLO, and RetinaNet Models. These models take the entire image as input and produce bounding box coordinates based on the object category at the output layer (Sultana et al. 2020).

7.2.1 YOLO (you only look once)

The YOLO model is widely utilized for object detection across various applications. It divides the input image into a fixed number of grid cells, as illustrated in Fig. 11 (Sultana et al. 2020). Each grid cell predicts a set number of bounding boxes, along with a confidence score that represents the product of the object detection probability and the Intersection over Union (IoU) between the predicted bounding box and the ground truth box. Bounding boxes with class probabilities exceeding a predefined threshold are selected, enabling precise object localization within the image. Several YOLO versions have been developed to enhance object detection accuracy while maintaining real-time performance. These include YOLOv2 (Redmon and Farhadi 2017), YOLOv3 (Redmon and Farhadi 2018), YOLOv4 (Bochkovskiy et al. 2020), YOLOv5 (Zhu et al. 2021), YOLOv6 (C. Li et al. 2022a, b), YOLOv7 (C.-Y. Wang et al. 2022), and YOLOv8 (Reis et al. 2023). Each iteration introduces refinements in feature extraction, bounding box regression, and model efficiency, improving detection accuracy and speed.

YOLO models have gained significant popularity in plant leaf disease detection. For instance, YOLOv3 has been used for tea disease detection (Bhatt et al. 2019), while YOLOv4 has been applied to citrus disease detection (Garcia and Barbedo 2013). However, YOLO's accuracy declines when detecting and localizing small targets. Bhatt et al. (2019) developed a YOLOv3-based approach for detecting pests and diseases in tea gardens under uncontrolled conditions. Using a self-collected dataset of 2,000 images depicting Tea Mosquito Bugs (TMB) and Red Spider Mites (RSM), the model achieved an 86% mAP at a 50% IoU threshold. YOLOv3 outperformed YOLOv2 in classification and localization tasks but was limited to tea plants. Maski and Thondiyath (2021) demonstrated that lighter

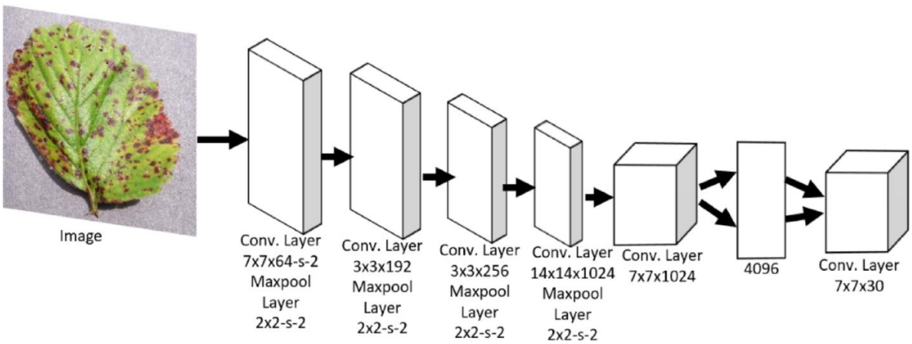


Fig. 11 YOLO Architecture (Redmon et al. 2016)

YOLO versions, such as tiny-YOLOv4 and MobileNetV2-YOLOv3, are more efficient for detecting papaya ringspot disease. They trained the models on a dataset of 2,000 images and found that tiny-YOLOv4 achieved the highest mAP of 99.9%, while MobileNetV2-YOLOv3 attained 98.39%, particularly for disease severity detection. J. Liu and Wang (2020) introduced an improved YOLOv3 model for tomato disease, insect, and pest detection. Their approach incorporated multi-scale feature detection, object bounding box clustering, and multi-scale training. The model achieved a detection accuracy of 92.39% with a processing time of 20.39 milliseconds, demonstrating robustness in complex environments. Yu et al. (2020) developed an R-YOLO model for a strawberry-harvesting robot, integrating MobileNet-V1 as a lightweight backbone. R-YOLO improved inference speed by 3.6 times compared to YOLOv3 and achieved an average recognition rate of 94.43% with a recall rate of 93.46%. However, detection performance declined when over 50% of the fruit was obstructed. Tian et al. (2019) enhanced YOLOv3 by incorporating DenseNet, optimizing low-resolution feature layers for apple detection. The YOLOv3-Dense model improved feature propagation and reuse, surpassing Faster R-CNN in detection accuracy. However, its complex structure increased execution time on embedded control devices, limiting real-time performance. Feng et al. (2022) proposed a two-stage identification model using YOLOv5 s for disease-spot detection, followed by a Bidirectional Cross-Modal Transformer (BiCMT) for classification. Training on 1,323 images and text records, the model achieved 99.23% accuracy, though cross-modal data imbalances affected identification outcomes. Shah et al. (2023) evaluated YOLOv5 and YOLOv7 for multi-class plant leaf disease detection using the PlantDoc dataset (2,598 images, 35 classes). YOLOv7 required significantly more processing power and exhibited high variability in mAP per epoch, achieving 42% mAP. In contrast, YOLOv5 performed more consistently, attaining a mAP of 62%.

7.2.2 Single shot multibox detector (SSD)

The SSD is a highly effective one-stage object detection algorithm. The SSD model utilizes a pair of 3×3 convolutional layers to predict class scores and location offsets for the default bounding boxes. To effectively identify objects of varying scales, SSD incorporates a sequence of increasingly smaller convolutional layers (Z. Li and Zhou 2017). This strategy enables the generation of pyramid feature maps, which are crucial for accurate object detection. Additionally, the anchor size is determined based on the receptive field size of the respective layers, ensuring appropriate scaling for object detection. Subsequently, the non-maximum suppression (NMS) technique is employed to perform post-processing on the final detection outcomes. The SSD algorithm is capable of real-time object detection and processes images faster than other advanced object detection methods due to its ability to detect objects from the plane ConvNet feature maps. The network architecture of SSD is illustrated in Fig. 12.

Sun et al. (2020) introduced an improved approach for detecting maize leaf blight in complex backgrounds using the SSD framework. Their method incorporates multi-scale feature fusion with CNNs to enhance detection accuracy. The proposed methodology consists of multiple stages, including data preprocessing, feature fusion, feature sharing, and disease detection. The model was evaluated on the NLB dataset, which contains 1,019 images with diverse angles and backgrounds, along with 7,669 annotations. The results demonstrated a mean average precision (mAP) of 91.83%, outperforming existing methods in both preci-

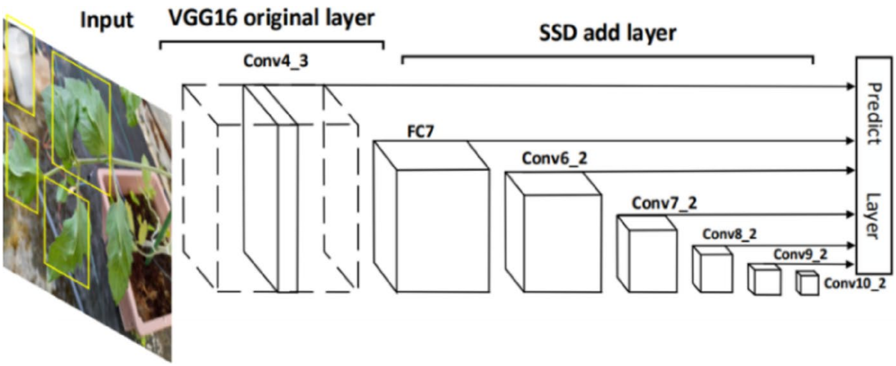


Fig. 12 The basic architecture of the SSD ((Liu et al. 2016)

sion and frames per second (FPS). Jiang et al. (2019) developed a deep CNN called INAR-SSD to enhance disease detection at multiple scales, particularly for small diseased regions. The model was trained to identify and classify five common apple leaf diseases. Tested on the apple leaf disease dataset (ALDD), which comprises 26,377 images, INAR-SSD achieved a detection performance of 78.80% mAP while maintaining a high speed of 23.13 FPS. Additionally, it demonstrated the ability to detect multiple diseases within a single image. Qiang et al. (2023) proposed a technique for citrus leaf disease identification using a double-backbone SSD model. The dual-backbone network significantly improved SSD's detection performance. Evaluated on 8,334 field-captured images, the model demonstrated strong robustness, achieving a mAP of 72.54%.

7.2.3 RetinaNet

RetinaNet is a one-stage object detection model that employs a focal loss function to address class imbalance during training (Lin et al. 2020). The focal loss method introduces a modulating factor into the cross-entropy loss function, prioritizing hard-to-classify negative examples. The model consists of a single, unified network comprising a backbone network and two specialized subnetworks. The backbone network applies convolutional operations to the entire input image, generating a convolutional feature map. Typically, this backbone is a pre-trained convolutional network. The first subnetwork performs convolutional object classification based on the backbone's output, while the second subnetwork is responsible for bounding box regression. Lin et al. (2020) proposed this streamlined approach for one-stage dense detection by integrating these two subnetworks. The architecture of RetinaNet is illustrated in Fig. 13.

Peng et al. (2022) proposed an improved RetinaNet model for detecting weeds among rice plants. The convolutional structure was modified to minimize semantic information loss, while the Efficient Retina Head was incorporated into the head network to reduce memory consumption and inference time. Additionally, the regression loss function was enhanced by integrating smooth loss with generalized intersection over union loss. Experimental results demonstrated an average weed recognition accuracy of 94.1%. However, the model did not fully utilize the information extracted from the backbone network, which weakened the correlation between feature maps, limiting its practical application. The data-

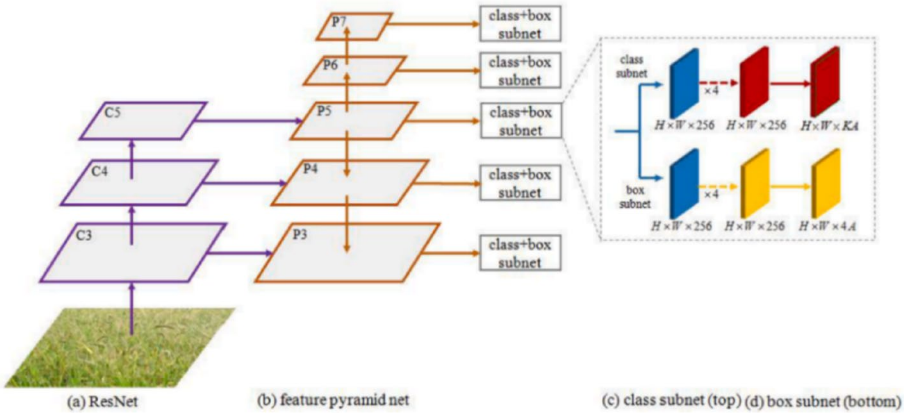


Fig. 13 RetinaNet network architecture (Lin et al. 2020)

set used for the experiment comprised 1,602 field-captured images of rice and weeds. Similarly, Pang et al. (2022) introduced an enhanced RetinaNet model designed to optimize the feature pyramid within the Feature Pyramid Network (FPN) and improve anchor generation for detecting wheat spider mites in wheat fields. The experimental results indicated a mean average precision (mAP) of 81.7%. However, a notable drawback of this approach was its inability to incorporate disease severity assessment.

In conclusion, among all the one-stage networks, YOLO is widely utilized for plant leaf disease detection due to its speed and efficiency in real-time detection, particularly for large datasets. Nevertheless, other one-stage networks also demonstrate strong performance, as summarized in Table 6.

8 Deep learning-based classification network

The application of deep learning methods for image classification has gained widespread popularity in agriculture due to their effectiveness in various tasks, such as detecting plant leaf diseases (KC et al. 2019). Deep learning-based classification is primarily conducted through supervised learning, where labeled image datasets are used to determine the class that best represents objects in the images. Image classification has been widely embraced by researchers across multiple disciplines, driven by the continuous development and application of diverse CNN architectures tailored for various use cases. This section discusses CNN-based approaches for plant leaf disease classification that have achieved significant advancements. Notable architectures include LeNet (LeCun et al. 1998), AlexNet (Krizhevsky et al. 2012), GoogLeNet, DenseNet, VGGNet, ResNet, MobileNet, and EfficientNet. These models vary in architecture, number of parameters, shape, and size, yet they have demonstrated effectiveness in detecting plant leaf diseases based on attributes such as size, shape, and colour. Additionally, these models facilitate feature extraction from plant images, aiding in the training of classifiers capable of accurately recognizing a wide range of plant diseases.

Table 6 Summary of the one-stage networks for plant disease detection

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Wan and Goudos 2019)	detection and classification of leaf spot disease in sugar beet	Self-acquired of sugar beet (155 images)	Faster R-CNN	Accuracy =95.48%	Faster R-CNN showed excellent performance in detecting and classifying sugar beet leaf spots, achieving a 95.48% accuracy.	Limited dataset size may hinder generalization across different plant species.
(Xie et al. 2020)	Grape leaf disease detection	Grape Leaf Disease Dataset (GLDD) (4,449 images)	Faster DR-IACNN model	mAP = 81.1%	The Faster DR-IACNN model enhanced feature extraction through Inception modules, achieving an mAP of 81.1% for grape leaf diseases.	Relatively lower frame-per-second (15.01 FPS) makes it unsuitable for real-time deployment in agricultural settings.
(Fuentes et al. 2017)	Tomato diseases and pest recognition	Tomato Diseases and Pests Dataset (5000 images)	Faster R-CNN	mAP = 85.98%	Demonstrated reliable performance across different tomato diseases and pests, with an mAP of 85.98%, making it useful for classification tasks.	High computational cost limits real-time deployment and scalability for larger farms.
(J. Li et al. 2023)	Strawberry	Self-acquired (1514 images)	Strawberry R-CNN	Accuracy = 99.1%	Strawberry R-CNN was highly effective in detecting strawberries with an accuracy of 99.1%, showing robustness in real-world settings.	Limited to strawberries; may not generalize effectively across other crops.

Table 6 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Maski and Thondiyath 2021)	Papaya	Self-acquired	Tiny-YOLOv4 and mobileNetV2-YOLOv3	mAP = 99.9% and mAP = 98.39%	Extremely high mAP (99.9% and 98.39%) using Tiny-YOLOv4 and mobileNetV2-YOLOv3 for papaya disease detection. Lightweight models allow for faster inference times, suitable for real-time applications.	The performance may drop when the model is applied to a different dataset or crop. The lightweight nature of the models may limit their ability to detect complex diseases or small features.
(J. Liu and Wang 2020)	Tomato diseases and insect pests	-	Improved version of the Yolo V3	Accuracy = 92.39%	High accuracy (92.39%) in detecting tomato diseases and pests using an improved version of YOLOv3. The improved YOLOv3 is effective in handling different image sizes and resolutions.	The model may underperform when detecting small or overlapping objects. While robust, the model's speed might be slower in real-time scenarios with high-resolution images.
(Y. Yu et al. 2020)	Ridge-planted strawberries	Self-acquired Strawberry (100 images)	Rotated YOLO (R-YOLO)	Accuracy = 94.43% Recall = 93.46%	High accuracy (94.43%) and recall (93.46%) using Rotated YOLO (R-YOLO) for ridge-planted strawberries. R-YOLO performs well in identifying precise picking points for harvesting.	Confidence scores may decrease significantly when fruits are obscured by leaves or other objects. The model is specialized for specific conditions, limiting its applicability to broader agricultural settings.

Table 6 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Tian et al. 2019)	Apple	Self-acquired	YOLOV3-dense model		The YOLOV3-dense model provides strong detection capabilities for apple disease detection.	High computational complexity and Inadequate for real-time deployment.
(Feng et al. 2022)		Self-acquired (1,323 images and 1,323 text)	YOLOv5s+BiCMT	Accuracy = 99.23% Precision = 97.37% Sensitivity = 97.37% Specificity = 99.54%	Extremely high accuracy, precision, and specificity, which makes the model highly reliable for real-world disease detection. Efficient at integrating image and text data, improving the accuracy of multimodal datasets.	An imbalance in cross-modal data can impact identification outcomes, potentially limiting the model's effectiveness in complex real-world scenarios.
(Shah et al. 2023)		Plantdoc dataset (2598 images)	Yolov5 and Yolov7	mAP = 62% mAP = 42%	Yolov5 demonstrates reasonable accuracy and real-time performance in multi-class disease detection. Yolov7 is a more advanced architecture that could offer better detection capabilities with further tuning. -	Yolov7 exhibits greater variability in performance and requires significant processing power, making it less suitable for low-resource environments. Lower mAP indicates that neither model performs consistently across all classes, limiting their robustness.

Table 6 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Sun et al. 2020)	Maize leaf	NLB dataset (1019 images)	SSD	mAP = 91.83%	The SSD model performs well on real-time detection tasks, making it ideal for applications requiring fast inference times. High accuracy for maize leaf disease detection in complex backgrounds.	Struggles with small objects in images, which could reduce its accuracy in datasets with intricate disease patterns.
(Jiang et al. 2019)		Apple leaf disease dataset (26,377)	INAR-SSD	mAP = 78.80%	INAR-SSD shows good performance on large datasets, especially with high-speed detection and classification of apple leaf diseases. Suitable for applications where detection speed is crucial.	Performance may decrease in detecting smaller lesions or when faced with diverse environmental conditions.
(Qiang et al. 2023)	Citrus leaves	Self-acquired (8,334 images)	İmproved-SSD	mAP = 72.54%	Shows robustness across various citrus diseases, even in real-world scenarios with field-collected data.	Lower mAP suggests that the model struggles with disease severity or fine-grained classification tasks.
(Peng et al. 2022)	Weeds	Self-acquired (1,602)	RetinaNet model	Accuracy = 94.1%	High accuracy, making it suitable for precise weed detection in agricultural fields. The focal loss function in RetinaNet addresses the class imbalance issue effectively.	Does not fully utilize information from the backbone network, which can limit its performance in more complex settings.

Table 6 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Pang et al. 2022)	Wheat spider mites	Self-acquired (9215)	RetinaNet model	mAP = 81.7%	Effective in detecting wheat spider mites, especially in real-world agricultural environments. Shows versatility across different datasets.	Limited ability to handle severe disease conditions or fine-tune detection for varying degrees of disease severity.

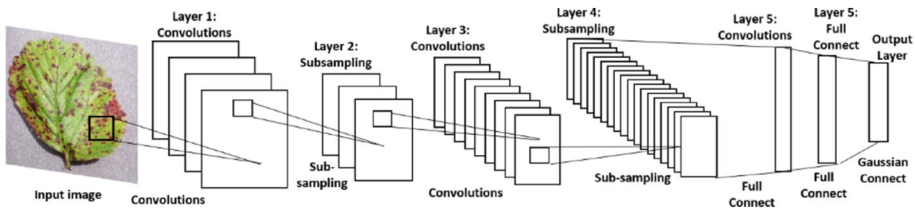


Fig. 14 The architecture of LeNet (LeCun et al. 1998)

8.1 LeNet model

LeCun et al. (1998) developed the LeNet CNN architecture, initially designed for recognizing handwritten digits (0–9) from the MNIST dataset. The architecture consists of seven layers, as illustrated in Fig. 14, including three convolutional layers (C1, C3, and C5), two average pooling layers (S2 and S4), one fully connected layer (F6), and an output layer. Over the past two decades, LeNet has been widely applied in various fields, including handwritten digit recognition (Mandal 2018; Y. et al. 1998), face detection (Dai et al. 2020; Zhang et al. 2023), and traffic sign recognition (Belghaouti et al. 2020; Somavarapu et al. 2023). Despite its effectiveness, LeNet encountered challenges in training due to the vanishing gradient problem. To address this issue, max pooling was introduced as a shortcut connection layer between convolutional layers, reducing spatial dimensions and minimizing the risk of overfitting. This enhancement enables more efficient CNN training. Figure 14 illustrates the LeNet architecture. Ahila Priyadharshini et al. (2019) introduced a modified version of LeNet designed for maize leaf disease classification. Using images from the PlantVillage dataset, their model achieved an accuracy of 97.89% in classifying maize leaves into three disease categories and one healthy class.

Wallelign et al. (2018) proposed a LeNet-based architecture for classifying diseases in soybean plants under varying environmental conditions. The authors evaluated the model using 12,673 leaf image samples from the PlantVillage dataset, achieving a classification accuracy of 99.21%. These findings highlight the effectiveness of LeNet in accurately identifying plant leaf diseases. Similarly, Amara et al. (2017) developed a LeNet-based model for detecting and classifying diseases affecting banana leaves. The model was trained on 1,643 banana leaf images from the PlantVillage dataset and demonstrated the ability to learn visual features directly from images. The study compared the performance of the model using coloured and grayscale images, revealing that the coloured images achieved a classification accuracy of 97.32%, while grayscale images reached 91.21%. However, the model was limited to correctly classifying only two types of diseased leaves.

8.2 AlexNet model

AlexNet was introduced by Krizhevsky et al. (2012) to effectively address the issue of overfitting. Its neural network architecture consists of eight layers, comprising approximately 650,000 neurons and 62.3 million learnable parameters. The first five layers include convolutional and max-pooling layers, while the last three layers are fully connected. The Softmax function is applied in the output layer, while the ReLU activation function is used after each intermediate layer. Figure 15 illustrates the architectural design of AlexNet. Durmus et al. (2017) utilized the AlexNet and SqueezeNet models to classify tomato leaf images from the PlantVillage dataset into ten categories, including healthy plants and nine disease types. Their findings indicate that AlexNet outperformed SqueezeNet slightly, achieving an accuracy of 95.65% compared to SqueezeNet's 94.3%. However, SqueezeNet demonstrated the advantage of operating with lower computational requirements, making it more suitable for deployment on mobile devices such as the Nvidia Jetson Tx1.

Maeda-Gutiérrez et al. (2020) compared the fine-tuning of AlexNet, Inception V3, GoogleNet, ResNet-18, and ResNet-50 for classifying tomato plant leaf diseases. Using 18,160 images from the PlantVillage dataset, the study found that AlexNet achieved the highest accuracy of 98.93%. Additionally, AlexNet demonstrated the fastest execution time, making it more efficient than the other architectures. The dataset used in this study contained nine distinct tomato disease categories along with a healthy class. Rangarajan et al. (2018a) developed a classification system for tomato crop diseases using pre-trained deep learning models, AlexNet, and VGG16. The study, which analyzed images from the PlantVillage dataset, reported high classification accuracy, with VGG16 achieving 97.29% and AlexNet attaining 97.49%. The model's performance was evaluated by adjusting parameters such as image quantity and learning rates, with the highest accuracy observed when using 373 images. Additionally, the results indicated that AlexNet achieved notable accuracy in a shorter execution time compared to VGG16.

Aravind et al. (2019) also utilized AlexNet to classify 4,063 grape leaf images into four categories: three disease types and a healthy grape leaf class. The pre-trained AlexNet model achieved a classification accuracy of 97.62%. Furthermore, the study extracted fea-

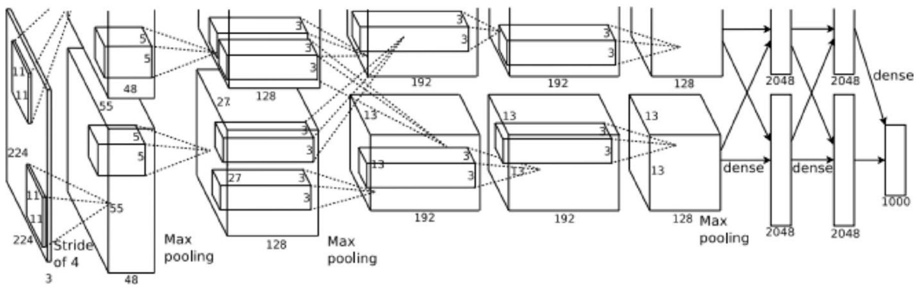


Fig. 15 The AlexNet Architecture (Alex et al. 2012)

ture values from various network layers and applied them to a Multiclass Support Vector Machine (MSVM), leading to an improved classification accuracy of 99.23%. Mohanty et al. (2016) proposed a transfer learning approach using a pre-trained AlexNet model to classify plant diseases effectively. The model demonstrated the ability to classify 26 distinct diseases across 14 different crop species accurately. Using a dataset of 54,306 images from the PlantVillage dataset, the model achieved an impressive accuracy rate of 99.35%.

8.3 GoogLeNet/Inception model

GoogLeNet, also known as Inception v1, was developed by Szegedy et al. (2015) and won the ILSVRC competition in 2014. The model addresses key challenges in conventional CNN architectures, such as vanishing gradients and the need to balance model depth with computational efficiency (Szegedy et al. 2015). It comprises nine inception modules, four convolutional layers, four max-pooling layers, three average pooling layers, five fully connected layers, and three softmax layers for auxiliary classification within the network, as illustrated in Fig. 16 (Mehdipour Ghazi et al. 2017). Additionally, the architecture incorporates dropout regularization in the fully connected layers and applies ReLU activation to each convolutional layer. Despite its increased depth and width comprising 22 layers, GoogLeNet has significantly fewer network parameters compared to AlexNet. Wu et al. (2020) employed a modified GoogLeNet with adjusted hyperparameters to classify tomato leaf diseases, including late blight (water mold), septoria leaf spot (fungus), target spot (bacteria), and YLCV (virus). When tested on the PlantVillage dataset, which consists of 1,500 tomato leaf images, the model achieved an accuracy of 94.33%.

Yang et al. (2023) introduced a GoogLeNet-based model, rE-GoogLeNet, for classifying rice leaf diseases. The rE-GoogLeNet model replaces the 7×7 convolution kernel in the first GoogLeNet layer with three 3×3 convolution kernels, effectively addressing gradient loss caused by network depth expansion and reducing information loss. To enhance feature extraction from diseased leaves with irregular shapes and small spots, the authors incorporated a leaky ReLU activation function. The study utilized 1,122 rice leaf images obtained from the rice pest database and Kaggle. Experimental results demonstrated that rE-GoogLeNet achieved a high classification accuracy of 99.58%. Zhang et al. (2018) developed an enhanced GoogLeNet and CIFAR-10-based model to improve the accuracy of maize leaf disease identification while minimizing network parameters. The models were trained and tested on nine types of maize leaf images. The modified GoogLeNet model

Fig. 16 The architecture of GoogLeNet (Wu et al. 2020)

achieved a top-1 average identification accuracy of 98.9% when evaluated on 500 images sourced from the PlantVillage dataset and Google. Brahimi et al. (2017) employed two neural network architectures, GoogLeNet and AlexNet, to classify nine tomato leaf diseases using 14,828 images from the PlantVillage dataset. The images were pre-processed by resizing and removing background information before classification. The extracted features were used for classification, achieving an accuracy of 99.18%. Maeda-Gutiérrez et al. (2020) compared the performance of fine-tuned state-of-the-art architectures, including GoogLeNet, AlexNet, ResNet-18, ResNet-50, and Inception V3. The dataset used in the experiments consisted of nine tomato disease classes and one healthy class sourced from PlantVillage. Among the models tested, GoogLeNet demonstrated the best results, achieving an AUC of 99.72% and a sensitivity of 99.12%. Based on these findings, the authors suggested that GoogLeNet holds significant potential as a tool for farmers to detect and protect tomato crops from diseases.

8.4 VGG net model

The Visual Geometry Group (VGG) was introduced in 2014 by Karen Simonyan and Andrew Zisserman from the University of Oxford (Simonyan and Zisserman 2015). Due to its simplicity and efficacy, VGG has attracted substantial recognition in computer vision and deep learning. The VGG architecture comes in multiple variations, namely VGG-16 and VGG-19, which differ in the number of layers. The simplicity of the structure makes VGG a highly proficient model for plant leaf disease classification. The VGG 16 and VGG19 architectures consist of stacked convolutional layers followed by fully connected layers. The models employ 3×3 filters with a stride of 1 and a max-pooling operation with a stride of 2 to decrease the spatial dimensions of the feature maps effectively. Figure 17 illustrates the architecture of VGG-19, which consists of 16 convolutional layers and three fully connected layers. The convolutional layers extract essential features from input images, while the fully connected layers classify the leaf images based on these extracted features. Meanwhile, the max-pooling layers help reduce feature redundancy and minimize the risk of overfitting.

Nguyen et al. (2022) employed VGG-19 with transfer learning to classify segmented tomato leaf images. Using 16,010 tomato leaf images from the PlantVillage dataset (nine disease classes and one healthy class), their approach achieved 99.72% accuracy while significantly reducing training time. The results highlight the model's effectiveness and potential for enhancement with more complex image datasets. Rangarajan et al. (2018b) applied pre-trained AlexNet and VGG-16 models via transfer learning to classify six tomato plant leaf diseases and a healthy class using PlantVillage data. AlexNet slightly outperformed

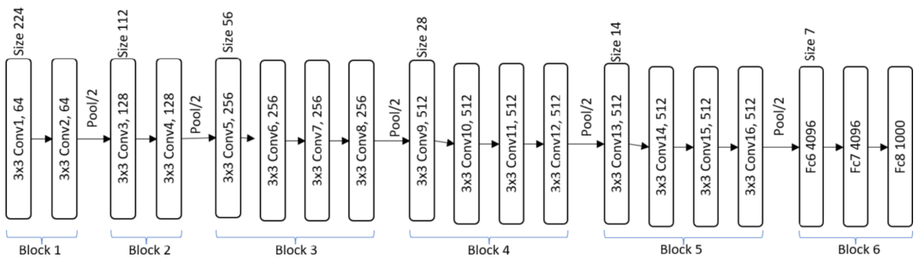


Fig. 17 The architecture of the VGG-19 model (Nguyen et al. 2022)

VGG-16, achieving 97.49% accuracy compared to 97.29%. Rinu and S. H. (2021) proposed a VGG-16-based method for detecting 38 distinct plant leaf diseases. Their optimized approach leveraged limited computational resources yet outperformed conventional models. Trained on PlantVillage images, it achieved a mean accuracy of 94.8%, demonstrating its robustness under challenging conditions.

Jangid and Sharma (2023) introduced a web-based application designed to identify rice plant leaf diseases using VGG-16. Their dataset included 4,500 field-collected images of healthy and unhealthy rice leaves. The model achieved 90% accuracy, with a comparative analysis showing that their approach reduced training time while maintaining high classification accuracy. Alatawi et al. (2022) proposed a VGG-16-based plant disease detection model, classifying 19 disease categories from PlantVillage data with 95.2% accuracy and a loss value of 0.4418. In a separate study, Zhong and Zhao (2020) implemented CNN architectures with transfer learning on a Raspberry Pi 4 to classify plant leaf images. Their study evaluated VGG-16, InceptionV3, MobileNetV2, ResNet50 V2, and Xception models on the 38-class PlantVillage dataset. Among the models, VGG-16 demonstrated superior performance, achieving a sensitivity of 90% and an overall accuracy of 90%.

Rasti et al. (2021) analyzed wheat and barley growth stages using three classifiers: a five-layer CNN, a pre-trained VGG-19, and an SVM. Their dataset covered 12 wheat stages and 11 barley stages. The results demonstrated significant classification accuracies, with the VGG-19 model achieving accuracy rates exceeding 90% for both crops. Yang et al. (2022) investigated automated image classification techniques to differentiate between broadleaf and grass weeds in alfalfa crops. The study aimed to provide a potential solution for managing weed infestations. The research evaluated four input image sizes, four CNN architectures (VGGNet, AlexNet, ResNet, and GoogLeNet), and four distinct network optimizers. The results indicated that all networks experienced a decline in classification accuracy as input image size increased. However, VGGNet emerged as the most effective classifier when trained with the optimal input size and optimizer, whereas ResNet exhibited the lowest performance. Kunduracioglu and Pacal (2024) used CNN and vision transformer models to classify grape leaf diseases using PlantVillage and Grapevine datasets. Their Swinv2-Base model achieved 100% accuracy, but the study noted limitations, such as dataset size constraints and reliance on digital images. Despite these challenges, automated disease detection proved to be highly precise, supporting early intervention and improved agricultural productivity.

8.5 ResNet model

Residual Networks (ResNet), introduced by He et al. (2016), have significantly influenced various machine learning tasks, particularly image classification. The primary goal of ResNet is to develop deep neural networks while mitigating the vanishing gradient problem. Its key innovation is the introduction of "residual blocks" or "skip connections," which enable the network to learn residual functions. This approach allows the model to compute the difference between the desired output and the current representation, improving training efficiency. ResNet follows the concept of residual mapping, ensuring the preservation of input-to-output relationships. It is available in multiple depths, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152 (Alzubaidi et al. 2021). Among these, ResNet-50 is the most widely used variant, consisting of 49 convolutional layers and a fully connected (FC) layer. The architecture employs shortcut connections, as illustrated in Fig. 18. Pre-trained ResNet models have been extensively applied to plant leaf disease identification. For instance, Arun Pandian and Kanchanadevi (2022) introduced a deep residual CNN with 197 layers, known as ResNet-197, to detect various plant leaf diseases. The model, structured into six layer blocks, was trained in a GPU environment for 1,000 epochs. To enhance the dataset, several preprocessing techniques were applied, including cropping, scaling, flipping, affine transformation, rotation, saturation adjustment, padding, and hue transformation. The augmented dataset comprised 154,500 images covering 103 distinct classes, representing both healthy and diseased leaves from 22 different plant species. (Kunduracioglu 2024b) utilized ResNet-based architectures to classify tomato leaf diseases using the PlantVillage dataset, which contains 13,875 images across multiple disease classes. Experimental results showed that Res2 Next50 achieved the highest accuracy (99.85%) and F1-score (99.82%), followed by Res2 Net50 d with an accuracy of 99.78%. These models outperformed other CNN architectures, such as VGG16 and DenseNet121, demonstrating superior precision and recall.

8.6 DenseNet model

DenseNet, introduced by Huang et al. (2017), effectively addresses some limitations of conventional CNN architectures, particularly vanishing gradients and inefficient feature reuse. This is achieved through an innovative approach known as “dense connectivity,” where each layer is directly connected to all subsequent layers (Kuang et al. 2019; Rubin et al. 2017). Unlike traditional CNNs or ResNet architectures, which rely on sequential connections or shortcut links, respectively, DenseNet enhances feature propagation while reducing the number of parameters. Due to these advantages, DenseNet has gained substantial recognition and has demonstrated superior performance in various computer vision tasks, including image classification, object detection, and segmentation. Figure 19 illustrates the

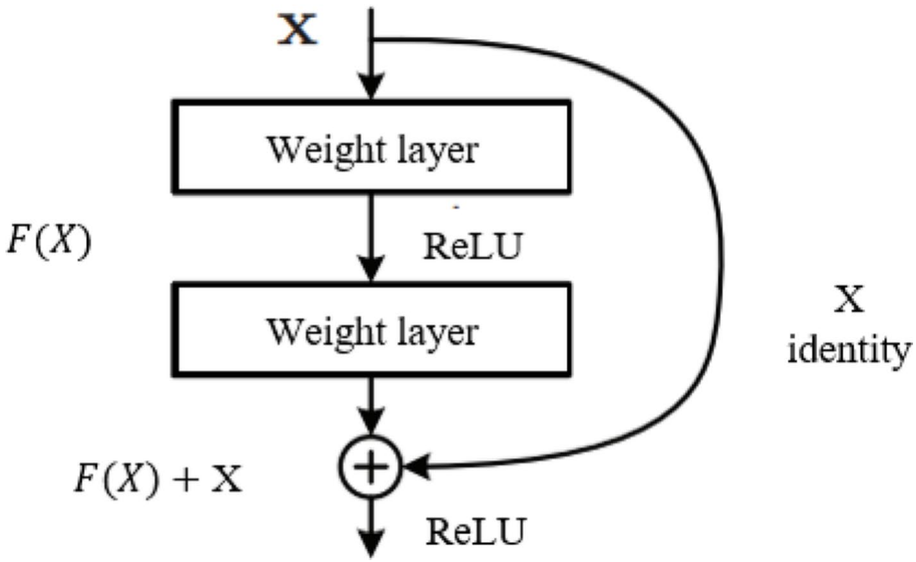


Fig. 18 The block diagram for ResNet (He et al. 2016)

DenseNet architecture. Tiwari et al. (2021) proposed an algorithm for plant leaf disease identification and classification using DenseNet. Their approach involved analyzing leaf images captured at different resolutions and training the model on a diverse dataset encompassing six crops and 27 categories in both laboratory and field conditions. The model was evaluated using five-fold cross-validation and tested on unseen data, achieving an average cross-validation accuracy of 99.58% and an average test accuracy of 99.19%.

Too et al. (2019) conducted a study on fine-tuning and evaluating deep convolutional neural networks (DCNNs) for classifying plant leaf diseases using the PlantVillage dataset. This dataset consists of 38 distinct classes, including both healthy and diseased leaves from 14 plant species. Their findings indicated that DenseNet exhibited continuous accuracy improvement with increasing epochs, minimal overfitting, and efficient parameter usage. The model achieved an accuracy of 99.75%, outperforming other architectures and demonstrating its effectiveness. Albattah et al. (2022) developed a plant leaf disease classification system using a custom CenterNet framework with DenseNet-77 as the base network. The system was trained on 54,306 plant leaf images from 14 plant species obtained from the PlantVillage dataset, achieving an impressive accuracy of 99.98%. However, the researchers noted that the model's computational requirements make it unsuitable for mobile device implementation.

Zhong and Zhao (2020) introduced three novel methods for identifying apple leaf diseases using the DenseNet-121 architecture. Their approach incorporated regression, multi-label classification, and a focus loss function. The model was trained on 2,462 images of six different diseases from the AI-Challenger-Plant-Disease-Recognition dataset. The proposed methods achieved accuracy rates of 93.51%, 93.31%, and 93.71%, surpassing conventional multi-classification methods, which attained an accuracy of 92.29%. Pillai et al. (2023) used a pre-trained deep transfer learning model based on DenseNet121 TLM to detect and classify plant leaf diseases. The model was trained on 20,639 images from the PlantVillage dataset, categorized into 15 classes representing three different plant species. Fine-tuning was applied to DenseNet121 and additional layers, achieving an accuracy rate of 97.38%. Sharma et al. (2022) used the DenseNet169 model to identify and classify diseases in cassava plant leaves. Their dataset comprised 21,397 images from the Kaggle platform. The model achieved a training loss of 0.1946 and a validation loss of 0.2952, with sensitivity and specificity values of 93% and 91%, respectively.

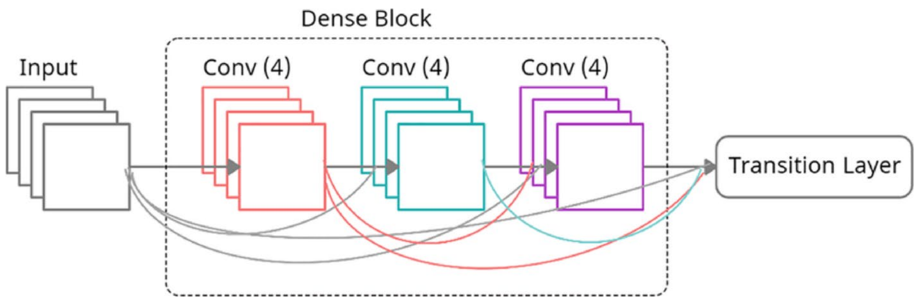


Fig. 19 DenseNet201 architecture (Ben Atitallah et al. 2022)

8.7 MobileNets model

Howard et al. (2017) introduced MobileNets, a highly efficient deep-learning model designed for mobile and embedded system applications. MobileNets utilize depthwise separable convolutions to construct lightweight neural networks, significantly reducing computational complexity while maintaining high accuracy. The developers incorporated two global hyperparameters to balance the trade-off between accuracy and computational efficiency, making MobileNets particularly well-suited for resource-constrained environments such as smartphones, edge devices, and Internet of Things (IoT) applications. Several iterations of MobileNet have been developed, each improving upon its predecessor: MobileNetV1 (Howard et al. 2017), MobileNetV2 (Sandler et al. 2018), and MobileNetV3 (Howard et al. 2017). These models have gained widespread adoption across various domains, including mobile vision applications, object recognition, autonomous vehicles, and augmented reality. Figure 20 illustrates the MobileNet architecture. Chen et al. (2020) introduced MobileNet-Beta, an enhanced approach for plant leaf disease identification. Their method improves upon the existing MobileNetV2 architecture by incorporating a classification activation map. The model's initial weights were preserved in the lower convolutional layers, while transfer learning techniques were applied to retrain the higher layers using a pre-trained model. The proposed model was evaluated on both the PlantVillage dataset and a custom dataset curated by the researchers. Experimental results demonstrated that MobileNet-Beta achieved an accuracy of 99.85% on the PlantVillage dataset and 99.11% on the custom dataset, highlighting its effectiveness in plant disease classification. Syamsuri and Kusuma (2019) developed a plant disease detection system designed for both personal computers and mobile devices. Their study compared the performance of three deep learning models: MobileNet, Mobile NASNet, and InceptionV3 on resource-limited devices to assess their suitability for real-world applications. The results indicated that InceptionV3 achieved the highest accuracy at 95.79% on mobile devices, followed by MNasNet at 94.87% and MobileNet at 92.83%. However, MobileNet exhibited the lowest latency at 394.70 ms, making it the most efficient in terms of processing speed. Based on their findings, the authors recommend using mobile phones for plant disease detection due to their practicality, low

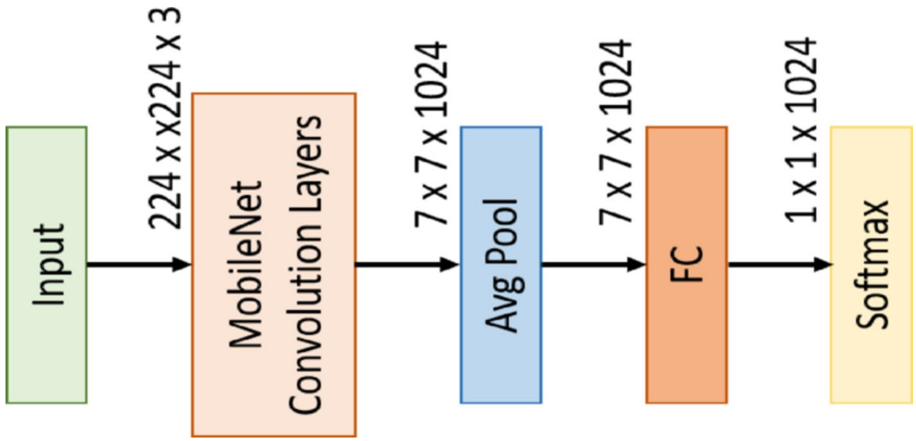


Fig. 20 Block diagram of the MobileNet architecture (Phiphiphatphaisit and Surinta 2020)

resource consumption, and minimal accuracy loss compared to desktop-based models. This approach enables fast and accessible plant disease identification, making it a viable solution for real-time agricultural applications.

8.8 EfficientNet model

EfficientNet, introduced by Tan and Le (2019), is a family of CNN architectures designed for high performance in image classification while maintaining computational efficiency. The core innovation of EfficientNet is compound scaling, which simultaneously adjusts the model's depth, width, and input resolution to achieve superior accuracy with fewer parameters compared to traditional CNNs. The architecture starts with a baseline model, EfficientNet-B0, which is progressively scaled up to EfficientNet-B7, with each variant offering increased complexity and computational power. These models have demonstrated state-of-the-art performance on benchmarks such as ImageNet and have been widely applied in object detection, segmentation, and other computer vision tasks. Their efficiency makes them particularly well-suited for resource-constrained environments. Figure 21 illustrates the block diagram of the EfficientNet model. Atila et al. (2021a) proposed an EfficientNet-based approach for classifying plant leaf diseases across 39 categories. Their study evaluated model performance using both the original and enhanced versions of the PlantVillage dataset, leveraging transfer learning techniques. Among the EfficientNet variants, the B5 and B4 models outperformed other deep learning architectures. The EfficientNet-B5 model achieved an accuracy of 99.91% and a precision of 98.42%, while the B4 model attained an even higher accuracy of 99.97% with a precision of 99.39%. These results highlight EfficientNet's potential for precise and efficient plant disease classification.

Farman et al. (2022) introduced an EfficientNet-based model for plant disease identification using fruit and leaf images. By adjusting the feature extraction pipelines of pre-trained networks, they optimized detection performance. The model was fine-tuned using a dataset from peach orchards and achieved an average accuracy of 96.6%, with sensitivity and precision of 90% and specificity of 98% on the test set. Duong et al. (2020) employed EfficientNet and MixNet classifiers for real-time fruit detection and classification in resource-constrained environments. Using a dataset of 48,905 training images and 16,421 testing images, their findings demonstrated that EfficientNet and MixNet significantly outperformed baseline models, improving predictive accuracy through randomization and transfer learning techniques.

Liu et al. (2020) optimized a maize leaf disease classification model using transfer learning. After preprocessing, they fine-tuned a pre-trained EfficientNet model on ImageNet by replacing the final layer with a softmax classifier. The dataset included 9,279 images from the AI Challenge dataset and online sources. Their approach improved training speed and achieved an accuracy of 98.85%. Reda et al. (2022) developed AgroAId, a mobile plant

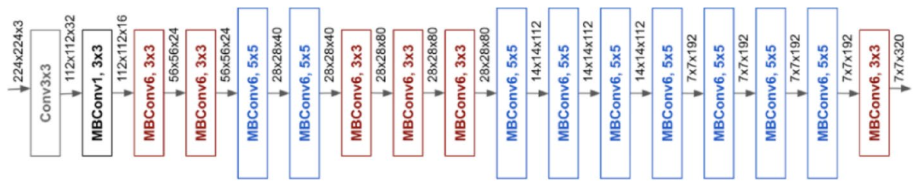


Fig. 21 Block diagram representation of EfficientNet (Atila et al. 2021a)

care support system leveraging computer vision for plant classification. They compared four lightweight CNN models- EfficientNetB0, MobileNet, MobileNetV2, and NasNetMobile on 61,486 images from the PlantVillage dataset across 39 classes. EfficientNetB0 proved the most accurate and computationally efficient, achieving 99% accuracy with an optimized base network and hyperparameters. Singh et al. (2022a, b) proposed an EfficientNetB3-based approach for identifying tomato leaf diseases. The dataset included 11 distinct leaf types from an online database. The model was trained using two optimizers, Adamax and Adam, over 15 cycles with a batch size of 32. EfficientNetB3 consists of six blocks, each containing distinct modules. The best results were obtained using the Adam optimizer, achieving an accuracy of 94%.

Kunduracioglu (2024a) investigated CNN models for classifying apple leaf diseases using the PlantVillage dataset, which contains 3,171 images. Of the models evaluated, EfficientNetV2_m achieved the highest accuracy and F1-score of 100%, surpassing all other architectures. This methodology enhances automated disease identification and crop management, though it is by the small dataset, increasing the risk of overfitting. In another study, İshak and İsmail (2024b) employed EfficientNet CNN models to classify sugarcane leaf diseases using the Sugarcane Leaf Dataset. EfficientNet-b6 attained the highest accuracy of 93.39% and an F1-score of 90.94%, outperforming Resnetv2-50 and Inception-V4. Table 7 provides a summary of existing deep learning-based classification research.

9 Performance evaluation metrics

9.1 Relevant hyperparameters

The key hyperparameters for deep learning models used in plant leaf disease detection and classification include learning rate, batch size, number of epochs, optimizer type, activation functions, dropout rate, regularization methods, weight initialization strategies, and loss functions, among others. Although these hyperparameters are not explicitly outlined in a separate table, they are discussed within the context of each model throughout this study. Each model's description highlights the key hyperparameters that significantly influence its performance and effectiveness.

9.2 Performance metrics

Evaluating the performance of deep learning models is essential for developing effective systems. The following performance metrics are used to assess the effectiveness of plant leaf disease classification models:

- Accuracy measures the proportion of correct predictions among the total instances evaluated. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- Loss function measures the error between predicted and actual values and is minimized

Table 7 Summary of research on the classification of plant diseases leaves-based

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Ahila Priyadharshini et al. 2019)	Maize leaves	PlantVillage	LeNet model	Accuracy = 97.89%	High accuracy of 97.89% using the LeNet model.	Limited to maize leaves; may not generalize to other plants or datasets.
(Badea et al. 2016)	Burn wounds in pediatric, Face recognition	The Burn Wound, paintings database, Kaggle facial keypoint detection, BioID facial database, PUT face	LeNet and Network in Network (NiN)	Accuracy = 75.91%	Utilizes multiple datasets and models (LeNet, NiN) for diverse applications.	Lower accuracy (75.91%) compared to other studies; focus is not solely on plant diseases.
(Wallelign et al. 2018)	Soybean plants	Plant-Village (12,673)	LeNet architecture	Accuracy = 99.21%	Very high accuracy of 99.21% with LeNet architecture.	Limited to soybean plants; may not be applicable to other crops.
(Amara et al. 2017)	Banana leaves	Plant-Village dataset (1643)	LeNet architecture	Accuracy = 99.32%	LeNet demonstrated high accuracy in classifying banana leaf diseases, particularly when applied to colored images, with an accuracy	Performance dropped when applied to grayscale images. Limited to detecting two diseases.
(Durmus et al. 2017)	Tomato crops	PlantVillage	AlexNet and SqueezeNet models	accuracy = 95.65% and 94.3%	Outperformed SqueezeNet in classifying tomato leaf diseases with a slightly higher accuracy (95.65%).	Computationally expensive, with slower processing times compared to other lightweight models like SqueezeNet.
(Maeda-Gutiérrez et al. 2020)	Tomato crops	Plant-Village (18,169)	AlexNet model	accuracy = 98.93%, sensitivity = 98.38%, precision = 98.74%, F-Score = 98.54%, specificity = 99.88%	Achieved impressive accuracy in classifying tomato crops, and the network's architecture allowed it to handle more complex images.	Complexity made it less suitable for real-time agricultural applications in resource-limited environments.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Rangarajan et al. 2018a)	Tomato crop diseases	PlantVillage (373)	AlexNet and VGG16 Net	Accuracy = 97.49% Accuracy = 97.29%	Use of AlexNet and VGG16 with high accuracy (97.49% and 97.29%).	Small dataset size (373 images); may not fully represent tomato crop diseases.
(Aravind et al. 2019)	Grape leaf images	Plant-Village (4063)	AlexNet architecture	Accuracy = 97.62% Accuracy = 99.23%	High accuracy with AlexNet (97.62% and 99.23%) on grape leaf images.	Limited dataset size (4063 images); specific to grape leaves.
(Mohanty et al. 2016)	Disease crops	Plant-Village (54,306)	AlexNet model	Accuracy = 99.35%	Achieves very high accuracy (99.35%) with AlexNet on a large dataset (54,306 images), demonstrating the effectiveness of the model in plant disease classification.	Focus on general crop diseases; may not provide specific insights for individual plant species or types. The dataset's broad nature might dilute the model's performance on specific diseases.
(Wu et al. 2020)	Tomato leaf	Plant-Village (1500)	GoogLeNet	Accuracy = 94.33%	Good accuracy (94.33%) with GoogLeNet for tomato leaves. Uses a well-regarded model architecture for effective disease detection.	Lower accuracy compared to some other models; might not be as effective with more complex or varied datasets. Limited to tomato leaves.
(Yang et al. 2023)	Rice leaf	Kaggle website (1086) Rice pest database (1122)	rE-GoogLeNet	Accuracy = 99.58%	Very high accuracy (99.58%) with rE-GoogLeNet on rice leaves. Provides an example of effective classification in a different crop category.	Mixed dataset sources (Kaggle and rice pest database) might affect consistency and model generalizability.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Zhang et al. 2018)	Maize leaf	Plant Village and Google websites (500)	GoogLeNet and Cifar10 models	Accuracy = 98.9%	High accuracy (98.9%) using GoogLeNet and Cifar10 models for maize leaves. Effective for maize but might offer insights for other crops as well.	Mixed dataset sources; accuracy may not be consistent across different types or conditions.
(Brahimi et al. 2017)		Plant-Village (14,828)	GoogLeNet and AlexNet	Accuracy = 99.18%	High accuracy (99.18%) with GoogLeNet and AlexNet, showcasing strong performance in plant disease detection.	Limited to PlantVillage dataset; model performance might vary with different datasets or crops.
(Maeda-Gutiérrez et al. 2020)		Plant-Village (54,323)	GoogleNet	AUC = 99.72% Sensitivity = 99.12%	Achieved impressive accuracy (99.72%) in classifying tomato diseases, and the network's architecture allowed it to handle more complex images.	The model's complexity might hinder its real-time application in resource-limited environments.
(Nguyen et al. 2022)	Tomato leaf	Plant-Village (16,010)	VGG-19 model	Accuracy = 99.72%	Highly accurate for plant disease classification (99.72%), with strong performance across multiple datasets.	High computational cost and longer training times due to its deep layers, limiting its practical deployment.
(Rangarajan et al. 2018b)	Tomato leaf	PlantVillage	VGG-16 model, AlexNet	Accuracy = 97.29% Accuracy = 97.49%	Provides accurate results (97.29% with VGG-16 and 97.49% with AlexNet) for tomato leaves. Useful for comparing different model performances	Results are specific to tomato leaves; small dataset size could affect generalizability.
(Rinu and S H, 2021)	Plant diseases	PlantVillage	VGG16 model	Accuracy = 94.8%	Achieves reasonable accuracy (94.8%) with VGG16. Shows effectiveness in plant disease detection.	Lower accuracy compared to some other models; dataset specifics are not detailed.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Jangid and Sharma 2023)	Rice plant	Self-acquired (4500)	VGG-16 model	Accuracy = 90%	Provides accuracy (90%) with VGG-16 on rice plants. Suitable for rice plant disease detection.	Lower accuracy compared to other models; performance might vary with different datasets or conditions.
(Alatawi et al. 2022)	Different crop	PlantVillage	VGG-16 architecture	Accuracy = 95.2% Loss value = 0.4418	Accuracy of 95.2% with VGG-16; includes loss value analysis for detailed performance evaluation.	Lower accuracy compared to top models; limited dataset details.
(Mora et al. 2021)	Pest and plant	PlantVillage	VGG16, InceptionV3, MobileNetV2, ResNet50 V2, and Xception models	Accuracy = 90% Sensitivity = 90%	Evaluates multiple models (VGG16, InceptionV3, MobileNetV2, etc.) with 90% accuracy. Provides a comparative analysis of different architectures.	Lower overall accuracy; results may vary with different datasets.
(Rasti et al. 2021)	wheat and barley	Self-acquired	VGG19 network, SVM	Accuracy = 90%	Good accuracy (90%) with VGG19 and SVM for wheat and barley. Suitable for a different crop category.	Lower accuracy compared to some other models; dataset specifics are not detailed.
(Yang et al. 2022)	Alfalfa, Broadleaf and grass weeds	Self-acquired	VGGNet, AlexNet, ResNet, and GoogLeNet	Nil	Uses multiple models (VGGNet, AlexNet, ResNet, GoogLeNet) on various weeds. Provides insights into model performance across different types.	No specific performance metrics provided; results might not be fully representative.
(Arun Pandian and Kanchanadevi 2022)	Tomato leaf	154,500 images	ResNet197	Accuracy = 99.58%	High accuracy (99.58%) with ResNet197 on a large dataset (154,500 images). Demonstrates strong performance in tomato leaf classification.	High computational demands of ResNet197; may not be applicable to other plant types.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Balavani et al. 2023)		Plant-Village (87,000)	ResNet-50	Accuracy = 99.3%	Very high accuracy (99.3%) with ResNet-50 on a large dataset (87,000 images). Effective for large-scale classification.	Performance may vary across different crops and conditions.
(Tiwari et al. 2021)	Apple, Potato, Tomato, Rice, and Citrus	Plant-Village (26,590), bean leaf (1296), Citrus leaf (609), and Rice leaf images (120)	DenseNet architecture	Accuracy = 99.19% cross-validation accuracy = 99.58%	Provided superior classification accuracy with fewer parameters compared to other deep networks, excelling in disease detection tasks.	Memory-intensive, making it challenging to deploy in real-time systems due to its densely connected architecture.
(Yang et al. 2022)	Alfalfa, Broad-leaf and grass weeds	Self-acquired	VGGNet, AlexNet, ResNet, and GoogLeNet	Nil	Uses multiple models (VGGNet, AlexNet, ResNet, GoogLeNet) on various weeds. Provides insights into model performance across different types.	No specific performance metrics provided; results might not be fully representative.
(Too et al. 2019)	Plant disease	Plant-Village (54,306)	DenseNets121, VGG 16, ResNet50, ResNet101, ResNet152, and InceptionV4	Accuracy = 99.75%	Showcased excellent performance on the PlantVillage dataset, achieving high accuracy, with its residual connections allowing for deeper network training without the vanishing gradient problem.	The complexity of the network increases computational requirements, posing challenges for deployment in low-resource environments.
(Albattah et al. 2022)	Plant leaf	Plant-Village (54,306)	DenseNet-77	Accuracy = 99.98%	Exceptional accuracy (99.98%) with DenseNet-77 on a large dataset (54,306 images).	:** Limited to one model and dataset; may not generalize to other plants or conditions.
(Zhong and Zhao 2020b)	Apple leaf	AI-Challenger-Plant-Disease-Recognition (2,462)	DenseNet-121: Regression, Multi-label classification, and focus loss function	Accuracy = 93.51% Accuracy = 93.31% Accuracy = 93.71% Cross-entropy loss function = 92.29%	High accuracy (98%) with a two-stage identification method. Effective for complex scenarios.	Model complexity might require higher computational power; limited applicability to other plants.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Pillai et al. 2023)	Plant leaf	Plant-Village (20,639)	DenseNet121 TLM	Accuracy = 97.38%	Good accuracy (97.38%) with DenseNet121 TLM.	Performance may vary depending on dataset and conditions.
(R. Singh, Sharma, Sharma et al. 2022)	Cassava plant	Kaggle platform, (21,397)	DenseNet169	Sensitivity = 93% specificity = 91%	High accuracy (93% sensitivity, 91% specificity) with DenseNet169 for cassava.	Performance metrics are lower compared to some models; specificity and sensitivity could be improved.
(Chen et al. 2020)	Apple, Potato, Grape, Tomato, Rice and Maize	Self– acquired (1000) and Plant-Village (54,306)	MobileNet-Beta	Accuracy = 99.85% Accuracy = 99.11%	Very high accuracy (99.85%) using MobileNet-Beta.	The performance may vary with different datasets.
(Syamsuri and Kusuma 2019)	Coffee leaf	PlantVillage	MobileNet, Mobile NASNet, and InceptionV3	MobileNet at 92.83% MNasNet at 94.87% InceptionV3 at 95.79%	Good performance with MobileNet, MNasNet, and InceptionV3 models.	Accuracy is lower compared to other models; variability in results.
(Atila et al. 2021a)	Plant leaf	Plant-Village (55,448) Augmented dataset (61,486)	EfficientNet: B4 and B5	B4: Accuracy = 99.97% Precision = 99.39% B5: Accuracy = 99.91% Precision = 98.42%	High accuracy (99.97% and 99.91%) with EfficientNet-B4 and B5 models.	Higher computational requirements; precision values slightly lower.
(Farman et al. 2022)	Peach leaf	Peach orchards	EfficientNet	Accuracy = 96.6% Sensitivity = 90% Specificity = 98%	Good accuracy (96.6%) with EfficientNet for peach leaf.	Sensitivity is lower (90%) compared to other models.
(Duong et al. 2020)	Multi plant	Fruits-360 dataset (48,905)	EfficientNet and MixNet	Nil	Use of EfficientNet and MixNet with a large dataset.	Performance metrics not detailed; effectiveness of MixNet is unclear.
(Liu et al. 2020)	Maize plant	AI Challenge dataset (9,279)	EfficientNet	Accuracy = 98.85%	High accuracy (98.85%) with EfficientNet for maize plants.	Limited to maize; performance may vary with different crops.

Table 7 (continued)

Reference	Area	Dataset	Techniques	Accuracy	Advantages	Disadvantages
(Reda et al. 2022)	Cassava, Citrus, Cotton, Coffee, etc.	PlantVillage (61,486)	AgroAId: EfficientNetB0 model	Accuracy = 99%	High accuracy (99%) with EfficientNetB0 for multiple crops.	Specific performance details are not provided; dataset specifics are broad.
(R. Singh, Sharma, Anand et al. 2022)	Tomato plant	Online database	EfficientNet B3	Accuracy = 94%	High accuracy (94%) with EfficientNetB3 for tomato plants.	Indepth performance details not provided; online dataset specifics are broad.
Kunduracioglu, (2024a)	Apple plant	PlantVillage (3,171)	EfficientNetV2_m	Accuracy = 100%	High accuracy (94%) with EfficientNetV2_m for apple plant	Limited dataset having the risk of overfitting
(Kunduracioglu 2024b)	Tomato plant leaf	PlantVillage (13,875)	Res2 Next50	Accuracy = 99.85%	The approach enhances automated disease detection, reduces human effort	Constrained by dependence on a single dataset
İshak and İsmail (2024b)	Sugarcane leaf	Sugarcane Leaf Dataset (6,748)	EfficientNet CNN models	Accuracy = 93.39%	High accuracy (94%) with EfficientNet-b6 for sugarcane	Increased complexity did not consistently correlate with improved accuracy and thus requires computational power.

during model training to improve accuracy.

- Precision represents the proportion of correctly predicted positive instances out of all predicted positives and is represented as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

- Recall (Sensitivity) measures the proportion of actual positive instances that are correctly classified. It is expressed as:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

- F1-Score is the harmonic mean of Precision and Recall, providing a balanced measure of both. It is calculated as:

$$\mathrm{F1-score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

- Specificity measures the proportion of actual negative instances that are correctly classified. It is represented as:

$$\mathrm{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

- Mean Average Precision (mAP) is commonly used in object detection and information retrieval tasks, including plant leaf disease detection when bounding boxes are involved. It evaluates the model's ability to detect and classify objects across multiple categories and is computed as:

$$mAP = \frac{1}{N} \sum{}_{i=1}^{N} AP_i \tag{6}$$

where TP, TN, FP, and FN represent True Positive, True Negative, False Positive, and False Negative, respectively, and N is the number of classes.

10 The practical implementation of deep learning models on real farms or in agricultural research

The implementation of DL models for plant leaf disease detection is gradually transitioning from experimental setups to real-world applications on farms. As precision agriculture becomes more prominent, CNNs and other deep-learning techniques offer promising solutions for improving crop management and disease control. While these models provide significant benefits in agricultural research and farm settings, they also present challenges that must be carefully addressed.

10.1 Deployment of mobile-based applications

Several mobile applications leveraging deep learning models have been developed for plant leaf disease detection, allowing farmers to capture crop images using smartphones and receive automatic disease diagnoses. Notable CNN models used in these applications include MobileNet, SqueezeNet, and EfficientNet, which enable real-time disease classification (Fu et al. 2024; Rajabu et al. 2022). The accessibility of these tools empowers farmers, even in remote areas, to diagnose diseases and take corrective action without needing specialized knowledge. These applications provide real-time monitoring and rapid feedback and extend precision agriculture to a wider audience, especially in resource-limited settings. However, mobile devices have computational limitations, requiring lightweight models that may compromise accuracy or complexity.

10.2 Integration with drones

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are increasingly being integrated with deep learning models for plant leaf disease detection. Drones capture aerial images of large fields, which are then processed using CNN models to identify diseased areas. For instance, fully convolutional networks (FCNs) have been applied to detect vineyard mildew in expansive vineyards, while the YOLO model has been used for real-time pest and disease detection in tea gardens using drone-captured images (Abbas et al. 2023; Chin et al. 2023; Kouadio et al. 2023). UAVs offer the advantage of monitoring large areas with minimal labor, making them particularly beneficial for large-scale farms. However, factors like weather conditions and lighting variations can affect image quality, leading to potential inaccuracies. Additionally, the cost of deploying drones and related technologies may be prohibitive for small-scale farmers.

10.3 Sensor-based monitoring systems

DL models are increasingly integrated into Internet of Things (IoT) platforms for continuous plant health monitoring. Sensors deployed across farms gather environmental data such as humidity, temperature, and soil moisture, which deep-learning models process to predict disease outbreaks before visible symptoms appear. Combining CNNs with weather and sensor data has proven effective for the early detection of diseases like potato blight (Chandan et al. 2022; Mahlein 2016; Mohammad-Razdari et al. 2022; J. Zhang et al. 2019). These sensor-based systems provide real-time monitoring, allowing for early intervention, particularly for diseases influenced by environmental factors, such as fungal infections. However, challenges such as high installation and maintenance costs, as well as the need for reliable power and internet connectivity, can limit their adoption in certain farming regions.

10.4 Field trials and agricultural research centers

Agricultural research centers are conducting field trials to evaluate the effectiveness of deep learning models in real farm conditions. For example, the performance of VGG16, InceptionV3, and EfficientNetB0 was tested for classifying three chili leaf diseases: upward curling, mosaic/mottling, and bacterial spot (Rozlan et al. 2022). The study used 3,000 chilli leaf images collected from three different field environments in Selangor, Malaysia. These images featured complex backgrounds, varying lighting conditions, angles, and distances to mimic real-world scenarios. The models achieved high accuracy, with InceptionV3 performing best at 98.83%. Similarly, Rozlan and Hanafi (2022) evaluated Faster R-CNN for detecting grape diseases in vineyards. These trials help refine models to handle field-specific challenges like background clutter, occlusions, and lighting variations. While field trials provide crucial insights into model robustness and adaptation for different crops, they are resource-intensive, requiring controlled environments and expert validation.

11 Discussion on challenges, trends, and advancements

The identification and classification of plant leaf diseases are crucial and complex in the field of plant pathology, mostly due to factors such as limited datasets, external noise, the resemblance of symptoms among various diseases, and the need for efficient detection. Nonetheless, researchers have achieved substantial advancements in this domain in recent years, leading to the development of diverse approaches to plant leaf disease classification. Notable advancements encompass DL methods, such as CNNs, which have demonstrated exceptional efficacy in disease identification and classification (Sundararaman et al. 2023). Furthermore, integrating multiple methodologies has fostered a more comprehensive approach to disease identification and categorization, improving accuracy and robustness (Sundararaman et al. 2023).

11.1 Discussion on current research studies

The literature on plant disease analysis shows a strong preference for classification methods (57%), indicating that most studies focus on categorizing diseases into predefined classes. This emphasis suggests that researchers prioritize identifying specific plant diseases, which is crucial for targeted treatment and management (see Fig. 22). Detection (36%) is also significant, playing a vital role in early disease recognition. In contrast, segmentation (7%) is less explored, likely due to its complexity and higher computational demands. The research gap in segmentation suggests opportunities for improving disease severity assessment and enhancing detection precision.

As shown in Fig. 23, research on plant disease detection is unevenly distributed across species. Tomato (19%) receives the most attention, followed by multi-plant studies (12%),

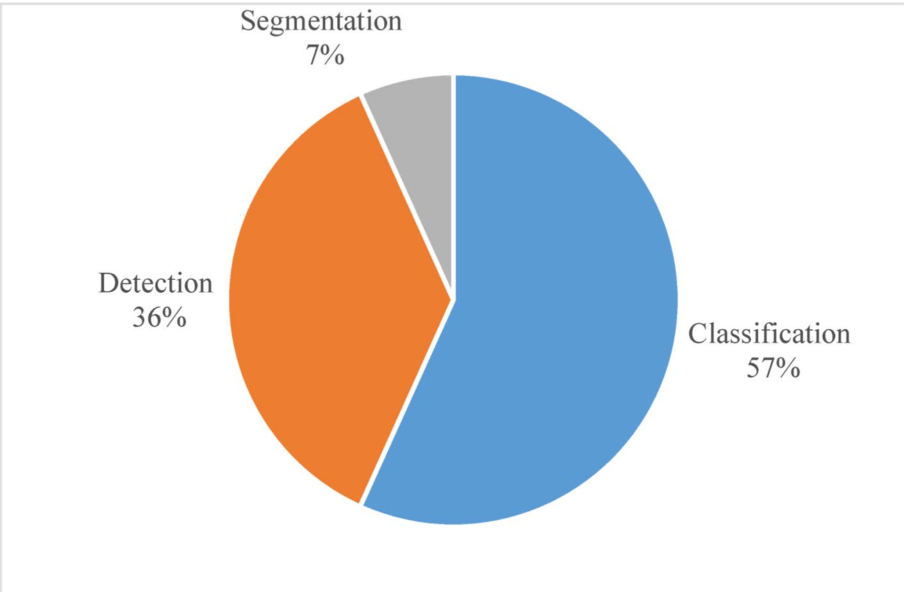


Fig. 22 DL base model used in literature

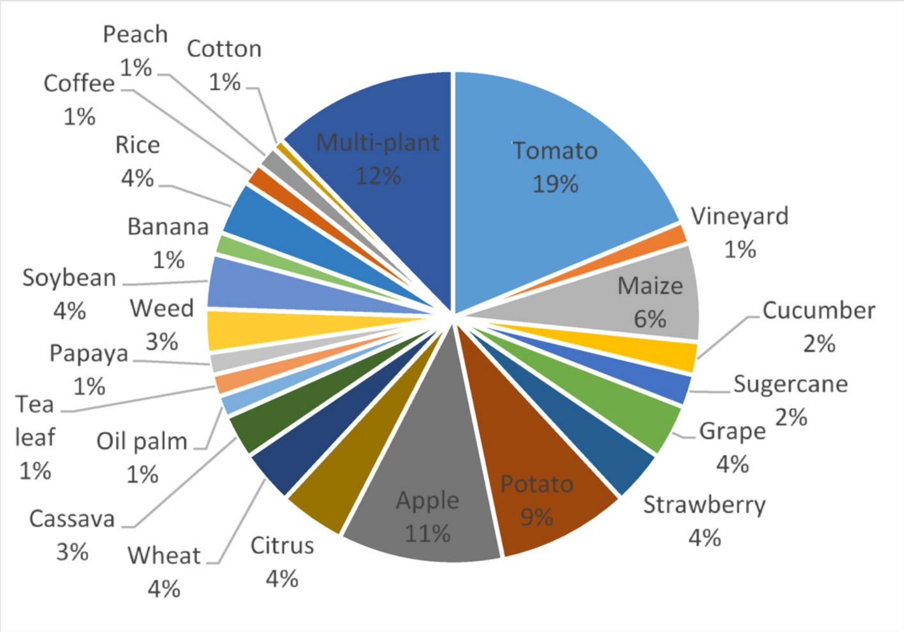


Fig. 23 Plants used in studies that applied to segment, detect, and classify plant leaf disease

apple (11%), and potato (9%). Maize (6%) stands out among cereals, while several crops, including rice, soybean, and wheat (4% each), receive moderate focus. Lower percentages (1–3%) for crops like vineyard, oil palm, and coffee suggest limited research, possibly due to regional cultivation or dataset availability. The distribution reflects the economic value and plant disease severity, highlighting the need for more studies on underrepresented crops.

11.2 Challenges in existing systems of plant leaf disease detection using CNNs

In the literature, several specific challenges that impact the effectiveness and generalization of CNNs in plant leaf disease detection have been identified. These challenges are drawn from both the datasets used and the methodologies constraints in existing studies..

i. *Dataset Limitations and Variability*: One of the primary challenges is the variability and limitations of the datasets used for training CNN models. For instance, the widely used PlantVillage dataset, despite its popularity, has limitations, such as images captured under controlled conditions with simple backgrounds. This simplicity can lead to models that perform well in controlled environments but struggle in real-world scenarios with complex backgrounds and varying lighting conditions. (Hughes and Salathe 2015) highlight that such limitations hinder generalization, as real-field conditions introduce factors like background noise and lighting variations that significantly impact model performance.
ii. *Generalization of Diverse Environmental Conditions*: Another challenge is ensuring CNN models generalize effectively across different environmental conditions. Studies

by Hasan et al. (2020) and Picon et al. (2019) demonstrate that models trained on datasets with limited environmental variability often fail when deployed in real-world settings. For example, Picon et al. (2019) integrated contextual metadata such as weather conditions and crop type into their CNN models, which improved accuracy. However, the challenge persists, as many existing models remain insufficiently robust to handle the diverse conditions found in agricultural fields.

iii. *Detection of Small Lesions and Early Disease Stages*: Detecting small lesions or early-stage diseases is another significant challenge. J. Liu and Wang (2021) noted that most CNN models require large, clear lesions for accurate detection, making early-stage diseases or small lesions difficult to detect. This limitation is particularly concerning for crops where early detection is crucial for effective management and control.

iv. *Scalability and Computational Complexity*: Scalability and computational complexity pose major challenges, particularly for large-scale deployment in agricultural settings. Studies by Fuentes et al. (2017) and Xie et al. (2020) show that while complex models like Faster R-CNN achieve high accuracy, they are computationally intensive and require significant resources, making them less feasible for resource-constrained environments, where real-time processing is often essential to prevent economic losses.

v. *Challenges with Feature Extraction and Model Overfitting*: CNN-based models rely on automatic feature extraction, which can sometimes lead to overfitting, particularly when training datasets are small. J. Liu and Wang (2021) and Shoaib et al. (2023) highlight that while CNNs are highly effective for automatic feature extraction, their performance heavily depends on the availability of large datasets. When the dataset sizes are limited, there is a risk of overfitting, where the model learns to recognize patterns that are specific to the training set but fails to generalize to new, unseen data.

vi. *Limitations in Dataset Augmentation and Preprocessing*: To address the issue of limited datasets, researchers commonly use data augmentation, but these approaches introduce their challenges. Studies by Hasan et al. (2020) and Jackulin and Murugavalli (2022) indicate that while augmentation methods improve model robustness, they may also introduce noise or artifacts that mislead the model during training. This issue is particularly pronounced in agricultural datasets, where plant appearances vary due to different growth stages and environmental conditions.

vii. *Impact of Noisy and Misclassified Data*: Another challenge is the presence of noisy or misclassified data within datasets. For example, the PlantDoc dataset includes images collected from the internet, which often lack expert-verified labels. G. B. Singh and Rani (2020) emphasize that misclassified or poorly labeled data can negatively affect CNN model training, reducing accuracy and reliability. This challenge suggests the need for improved data curation and labeling processes to ensure model accuracy and reliability.

viii. *Challenges with High-Resolution Images*: High-resolution images are often needed for precise plant disease identification, but processing such images requires significant computational power. Studies by Wang et al. (2019) and Maski and Thondiyath (2021) Note that while models like YOLO and Faster R-CNN can handle high-resolution images, their computational demands can be prohibitive for real-time applications, especially in resource-constrained environments. Addressing this challenge requires balancing image resolution with inference speed.

ix. *Difficulty in Detecting Mixed Diseases*: Another specific challenge is detecting multiple diseases affecting a single plant. Xie et al. (2020) highlight that CNN models often struggle when multiple diseases are present in the image or plant. Overlapping symptoms or lesions may confuse the model, leading to misclassification or reduced accuracy. This issue suggests a need for more sophisticated multi-label classification approaches to enhance detection performance.

11.3 Real-world problems concerning plant leaf diseases

i. Plant leaf diseases pose significant global challenges, affecting food security, economies, and the environment. Below are some of the most pressing real-world problems associated with plant leaf diseases: *Food Security and Crop Yield Losses*: Plant leaf diseases account for 20–40% of global crop yield losses, contributing to food shortages and economic instability. Diseases such as wheat rust, late blight in potatoes, and citrus greening severely impact staple crop production, increasing hunger and malnutrition in vulnerable regions (Gai and Wang 2024).
ii. *Economic Losses for Farmers*: For many smallholder farmers, agriculture is their primary source of income. However, plant leaf diseases can lead to devastating financial losses, particularly when entire harvests are destroyed. Additionally, disease outbreaks increase production costs due to the necessity of pesticides, fungicides, and disease-resistant crop varieties (Nazarov et al. 2020).
iii. *Overuse of Pesticides and Environmental Damage*: The excessive use of chemical pesticides to control plant leaf diseases contributes to soil degradation, water pollution, and biodiversity loss. Moreover, the overuse of fungicides and bactericides accelerates pathogen resistance, complicating disease management (Gai and Wang 2024).
iv. *Climate Change and the Spread of New Diseases*: Rising temperatures, irregular rainfall patterns, and increased humidity create optimal conditions for plant pathogens. Climate change has facilitated the spread of plant leaf diseases to new regions, where crops and farmers are often ill-prepared to manage them effectively (Gai and Wang 2024).
v. *Delayed Disease Detection and Rapid Spread*: Early detection of plant diseases remains a significant challenge in many agricultural settings, allowing infections to spread before effective intervention measures can be implemented. Traditional manual detection methods are time-intensive, laborious, and prone to human error, leading to considerable crop losses (Padshetty and Ambika 2023; Shafik et al. 2023).
vi. *Limited Access to Advanced Disease Detection Technologies*: Despite advancements in deep learning and artificial intelligence (AI) for plant leaf disease detection, many rural farmers lack access to these technologies due to high costs and limited internet connectivity. This digital divide prevents small-scale farmers from leveraging precision agriculture solutions that could enhance crop health and yield (Shafik et al. 2023).
vii. *Trade Restrictions and Export Losses*: International trade regulations impose stringent phytosanitary measures to prevent the spread of plant leaf diseases. Countries experiencing disease outbreaks may face export bans on agricultural products, leading to significant economic losses and reduced global trade opportunities (Gai and Wang 2024).
viii. *Emergence of Resistant Pathogens*: The rapid evolution of resistant plant pathogens, such as fungicide-resistant wheat rust, poses a major threat to agriculture. These

pathogens evolve rapidly, diminishing the effectiveness of existing control measures and necessitating continuous research and the development of new disease management strategies (Sahu et al. 2021).

Plant leaf diseases remain a major global concern, affecting food security, economic stability, and environmental sustainability. Addressing these challenges requires advancements in early disease detection technologies, the adoption of sustainable disease management practices, and improved access to modern agricultural innovations to support farmers and safeguard global food production.

11.4 Advancements in plant leaf disease detection using deep learning models

Recent advancements in deep learning have significantly improved plant leaf disease detection. The following key innovations enhance accuracy, robustness, and real-world applicability:

i. *Feature Fusion*: Feature fusion combines features from multiple layers or models to capture both low-level details and high-level semantic features, improving the robustness and accuracy of disease detection models. By incorporating complementary features from different scales, this approach enhances the model's ability to identify diseases with subtle visual differences across various leaf regions. It is particularly beneficial for detecting diseases that manifest in diverse forms, making it more reliable for real-world applications (Ali et al. 2022; Sunil et al. 2023a 2023b).
ii. *Attention Mechanisms*: Attention mechanisms enable models to focus on the most relevant parts of an image, improving the detection of disease-affected areas while reducing background noise. In plant leaf disease detection, these mechanisms help the model to concentrate on critical features, such as lesions or discolorations, which are key indicators of infection. This enhances disease localization and classification, even in complex images with multiple objects or noisy environments (Alirezazadeh et al. 2023; Lee et al. 2020; Yang W. et al. 2024).
iii. *Multi-Scale and Multi-Resolution Models*: Multi-scale approaches process images at different resolutions, enabling models to capture both fine-grained details, such as small lesions, and broader patterns, like disease spread across a leaf. These models enhance disease detection at various scales, improving performance across diverse datasets. Multi-resolution models have proven effective in identifying diseases that appear as either small spots or large discolorations, making them adaptable to different disease characteristics (Dai G. et al. 2024; Li S. et al. 2022; Liu L. et al. 2024).
iv. *Transfer Learning with Domain Adaptation*: Transfer learning with domain adaptation allows knowledge transfer from a source domain, such as large image datasets, to a target domain, such as specific plant leaf disease datasets. This process aligns models with the unique characteristics of agricultural images, addressing variations in lighting, textures, or perspectives. It is especially beneficial for smaller plant leaf disease datasets, as it improves detection accuracy while minimizing the need for extensive labelled data (Al-Gaashani et al. 2024; Fan et al. 2022; Shafik et al. 2024).
v. *Ensemble Learning*: Ensemble learning combines multiple models to enhance predictive performance by aggregating their outputs, reducing variance and bias, and

improving overall accuracy. In plant leaf disease detection, ensemble models integrate CNNs with algorithms such as XGBoost or Random Forests, resulting in more reliable disease classification. This approach leverages the strengths of different models, optimizing detection accuracy (Ali, A. H. et al. 2024; Chithra and Pushparani, 2023; Gunduz and Yilmaz Gunduz, 2022; Nader et al. 2022).

vi. *Generative Adversarial Networks (GANs) for Data Augmentation*: GANs generate synthetic data to augment limited datasets, improving model generalization. In plant leaf disease detection, GANs create synthetic images of diseased plants, addressing the challenge of limited labeled data. These synthetic images enhance the model's ability to recognize new and unseen disease instances, improving real-world detection performance (Alshammari et al. 2024; Gandhi et al. 2018; Khare et al. 2024; Lamba et al. 2022; Lokesh et al. 2024).

vii. *Edge-AI and On-Device Processing*: Edge-AI enables deep learning models to run on edge devices, such as smartphones or drones, rather than relying solely on cloud processing. In agriculture, this facilitates real-time disease detection directly in the field. These models are optimized for low-latency and resource-constrained environments, allowing for rapid and efficient disease diagnosis without requiring constant internet connectivity (Kalbande et al. 2024; Khan et al. 2023; Silva et al. 2023).

viii. *Hybrid Deep Learning Models*: Hybrid models integrate deep learning techniques with traditional machine learning algorithms or other methods, such as wavelet transforms or support vector machines. In plant leaf disease detection, these models enhance performance by leveraging the advantages of both approaches. For example, CNNs can be used for feature extraction, while support vector machines handle classification. This integration improves detection capabilities, particularly for challenging datasets (Bezabih et al. 2024; Hukkeri et al. 2024; Prince et al. 2024; Saberi Anari, 2022; Sharma, P. et al. 2023; Thaiyalnayaki and Joseph, 2021).

12 Conclusion and future works

This paper explores the current advancements in detecting and classifying plant diseases using deep learning, a crucial approach for ensuring long-term food security. The review focuses on data sources and the application of deep learning techniques for disease detection and classification. It provides a comprehensive survey of various CNN models, including LeNet, AlexNet, GoogLeNet, DenseNet, VGGNet, ResNet, MobileNet, and EfficientNet, while also addressing the dataset acquisition process. The findings indicate that many existing models struggle to process raw images in their unstructured form. This survey aims to encourage researchers to adopt diverse deep-learning techniques for plant disease identification and classification. Most of the reviewed studies primarily analyze single-leaf images for disease detection. However, future research could explore multi-leaf images captured in a single frame under varying environmental conditions, such as temperature and humidity, to minimize the impact of external factors on disease classification.

This review consolidates the state-of-the-art advancements in CNN-based plant leaf disease detection and classification, focusing on architectures such as VGG, ResNet, and YOLO, along with datasets ranging from PlantVillage to Cardamom Plant. The analysis highlights the high accuracies achieved by these models while also addressing persistent challenges, including small dataset sizes and occlusion issues. By synthesizing insights from 533 studies filtered down to 107 key works, this review serves as a valuable resource for researchers. It provides guidance on selecting models based on specific requirements, such as ResNet for higher accuracy and YOLO for faster detection, while also facilitating access to relevant datasets.

Additionally, this review identifies gaps in existing research, highlighting opportunities for further innovation in the field. Several promising techniques could drive future advancements in plant disease detection. Data augmentation and transfer learning can mitigate dataset limitations, enabling detection in niche crops like cardamom. Advanced segmentation approaches, such as Mask R-CNN and multi-modal imaging, can improve detection accuracy in complex environments. High-resolution models with attention mechanisms may enhance the identification of small lesions, enabling early disease intervention. Furthermore, multi-crop generalization and lightweight architectures like EfficientNet present scalable solutions, making deep learning-based plant leaf disease detection more accessible to farmers. These directions encourage the development of practical, real-world systems aimed at reducing global crop losses and promoting sustainable agriculture.

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Declarations

Competing interests The authors declare no competing interests.

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