Review article

Deep Learning for Plant Disease Detection and Classification: A Systematic Analysis and Review

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Curr. Appl. Sci. Technol. 2024, Vol. 24 (No. 4), e0259016; https://doi.org/10.55003/cast.2024.259016

Received: 18 May 2023, Revised: 29 November 2023, Accepted: 30 January 2024, Published: 30 April 2024

Keywords

deep learning;

CNN;

leaf disease classification;

crop disease detection;

image datasets

Abstract

Detection and classification of leaf and crop diseases in a traditional way is a very laborious task as it involves a significant amount of physical work, huge expert manpower, and valuable time. Automatic systems are more accurate and require less time, labor, and physical work. Artificial intelligence and deep learning-based systems can help in the rapid detection and classification of plant leaf and crop diseases as they occur and help to reduce the hostile effects of disease on food security and the economy. In this systematic and state-of-the-art review, an in-depth study was performed to find and assess the use of different deep learning methods in leaf disease detection and classification. In this study, we exhaustively reviewed contemporary research work on leaf and plant disease detection and classification using deep learning methods performed by several researchers worldwide. Various deep-learning techniques with intermediate steps, public datasets, types of diseases detected and classified, types of plants used, performance metrics used to evaluate models, and achieved results are summarized. Finally, various challenges encountered in using deep learning methods were summarized along with some guidelines that will be helpful for future researchers in this area.

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1. Introduction

Agricultural development started about 1200 years ago and improved the way people lived. Development in the agricultural sector can reduce poverty, raise incomes, and ensure food safety for farm-based people around the world who are poor. Diseases in plants and crops may have an adverse effect not only on the quality and quantity of crops but also on the lives of people who depend on farming. Ultimately, serious plant diseases cause deterioration of national economic conditions and are very detrimental to the people's income and occupation in the agricultural sector. Therefore, the early detection and further management of plant diseases plays a significant role in crop damage prevention, along with boosting the quality and quantity of crops. Smart farming is mandatory to face the challenges incurred in areas such as agricultural productivity, environmental problems, sustainability, and food safety [1].

In the 21st century, when technology has been enriched with various artificial intelligence and computer vision-enabled techniques, many farmers still follow the traditional methods of disease detection in plant leaves and crops by visiting the field physically and analyzing anomalies with their bare eyes. These traditional methods of analyzing and recognizing diseases through experience have several difficulties [2]. A major drawback of the traditional methods is that it is impossible for a farmer to have sufficient knowledge and expertise of all plant diseases and treatment plans. To deal with the above-mentioned problems with traditional methods, various AI-enabled and CV-based automatic disease detection and classification systems have been proposed by researchers. Recent advancements in artificial intelligence (AI), computer vision (CV), machine learning (ML), and deep learning (DL) can assist in early, quick, and correct detection of plant diseases. In 2012, a new era of deep learning began with the proposal and performance analysis of various deep learning models like AlexNet, VGG Net, GoogleNet, ResNet, ZFNet, SegNet, ExceptionNet, YOLO, RCNN, Fast-RCNN, Mask-RCNN, and U-Net. These models have found a range of various applications such as image recognition, autonomous vehicle, and medical science [3, 4].

A bunch of research work has been carried out over the last decades using different deep learning-based models with diverse image pre-processing techniques on a variety of plant leaf and crop diseases. Most of the research work used the PlantVillage dataset for training and testing. Model trained with lab-conditioned images generally did not perform well on real-time images [5]. Real-world images of plant leaves and crop diseases may have complicated backgrounds which can deteriorate the performance of a deep learning model. Sometimes prominent features become invisible or overlap with other features, making feature extraction and selection a difficult task for the model [6]. Along with disease identification and classification, measuring the severity of a disease is also much more important for disease management and remedial action [7].

2. Basics of Plant Disease Identification and Recognition

Advancements in artificial intelligence (AI) and computer vision (CV) allow computer-aided systems to analyze and evaluate with greater accuracy than human does. Such machine can inspect accurately, interpret, classify, and detect images like a human brain does. Nowadays, most of the agricultural sectors have already started using AI-enabled technologies.

AI and CV-based systems can identify and detect plant diseases effectively based on salient features or symptoms of diseases. Classification, detection, and segmentation are three different tasks in plant leaf disease management[8]. Determining which category a disease belongs to is called classification. Classification only defines the category. Detection not only defines the category of a disease in an image but also specifies the location of a disease in the images. The disease area is marked with a rectangular box in Figure 1. In the segmentation, the disease area is separated by pixel-by-pixel labeling from the background and provides various information, i.e., area, length, and position of disease as shown in Figure 1.

Crops can be affected by various diseases during the different stages of life of a plant and diseases can have a devastating effect on gross yield production. There are many factors responsible for plant diseases, which can be categorized into two main divisions: biotic and abiotic factors as shown in Figure 2.

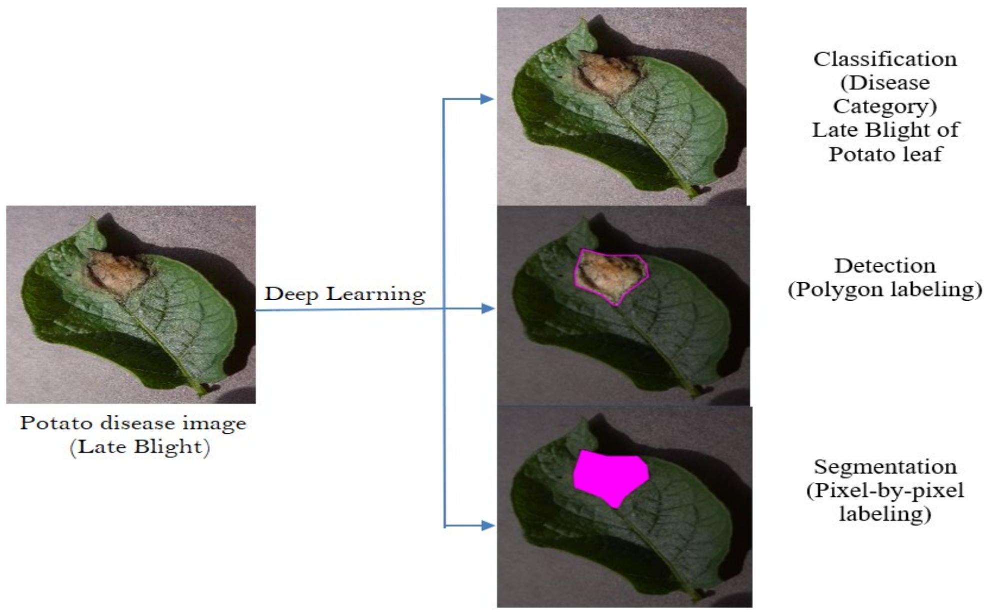

Figure 1. Leaf disease recognition problem with deep learning

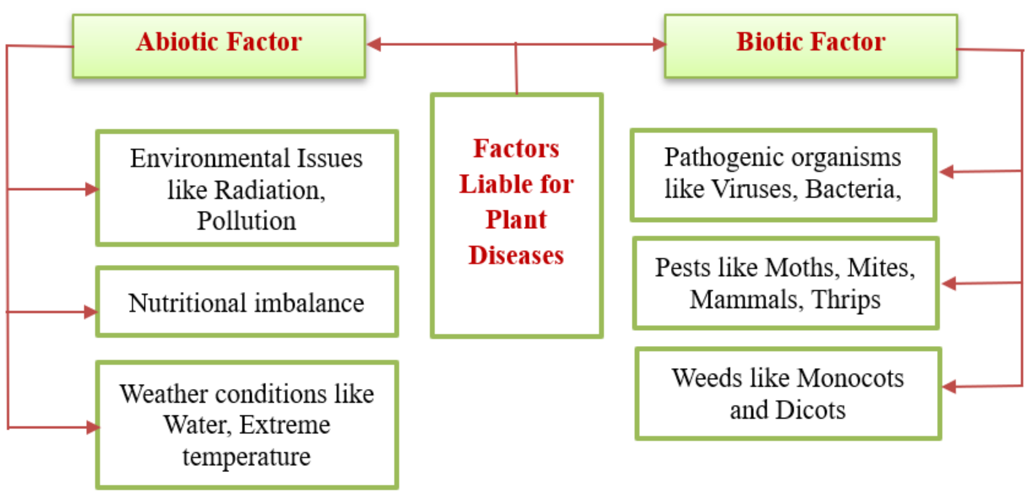

Figure 2. Possible factors for plant diseases

According to the dominating factors, plant diseases are divided into two major categories: biotic disease and abiotic disease. Biotic diseases are those diseases that arise because of biotic factors like insects, bacteria, fungi, mites, and viruses whereas abiotic diseases in plants arise due to environmental factors like water pollution, extremely high temperature, high humidity, nutrient deficiency, unacceptable soil pH, and greenhouses gasses [9].

3. Deep Learning for Plant Disease Analysis

We went through several recent papers that described deep learning-based plant disease identification and detection algorithms in this review study. The deep learning concept was first presented in a paper by Hinton and Salakhutdinov in 2006 [10]. The primary concepts of deep learning are as follows. A neural network is used to analyze data and extracts feature. The features are abstracted with multiple hidden layers (perceptron). The perceptron extracts low-level features and then combines the low-level features creating high-level features. Finally, these high-level features are used to classify and detect plant diseases. A deep learning-based system consists of a series of straightforward steps starting from preparing an image dataset and finally, classification and detection are performed using a trained deep learning model. Image dataset preparation involves image acquisition from the real field and/or taking images from publicly available datasets. This step is followed by various image pre-processing steps, splitting datasets (training, validation, and test sets), training the model using the training dataset, and validating the model. Figure 3 briefly describes the full approach used by most of the deep learning-based plant disease identification and recognition system.

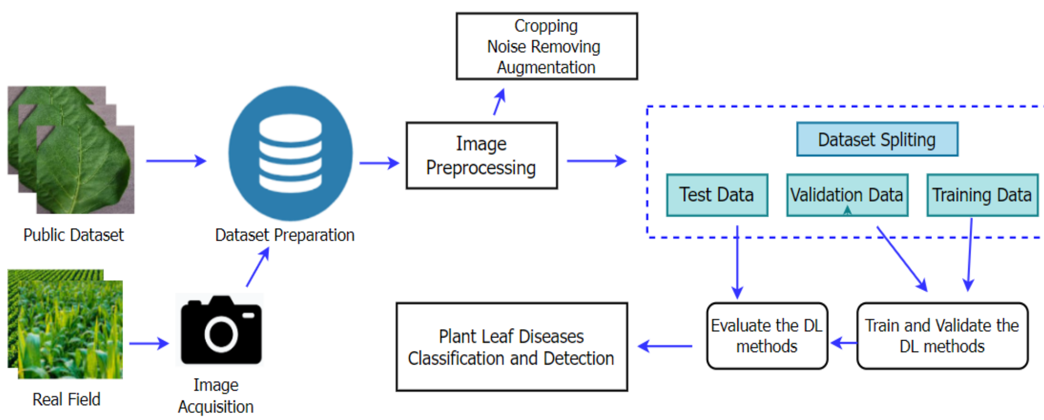

Figure 3. Pre-defined steps in DL-based plant leaf disease classification and detection

3.1 Comparison between deep learning and traditional image processing methods

Deep learning methods overcome the limitations of traditional image processing methods where features are selected automatically and have attracted the attention of researchers worldwide [11]. Therefore, deep learning models have already demonstrated their potential in plant disease identification and recognition. Extraction of deep and prominent features from the dataset using traditional image processing methods is difficult whereas deep learning models can be used to extract complex features automatically without human intervention. The differences between traditional image processing and deep learning methods are summarized in Table 1.

Table 1. Difference between traditional image processing methods and deep learning methods

Traditional Image Processing Method	Deep Learning Method
Manual feature design	Deep and complex features are learned automatically
Feature Extraction: SITF: HOG, LBP, shape, color, texture Classification: SVM, Bayesian, BP Image Segmentation: Threshold-based Segmentation, Robert, Prewitt, Sobel, Laplacian edge detection	Convolutional neural network model
Lower amount of data	Huge amount of data for training the model and high-performing machine
Poor identification and recognition as compared to deep learning methods.	Satisfactory performance as it can cope with deep and complex features.

SITF: Scale Invariant Feature Transform, HOG: Histogram of Oriented Gradients, SVM: Support Vector Machine, LBP: Local Binary Pattern

3.2 Deep learning tools

Many third-party open-source toolkits have been developed and used in the deep learning environment. Included are TensorFlow (TF), Caffe, Keras, CNTK, Torch, Theano, MXNet, and many others [12]. These deep-learning tools support multi-core processors (CPUs) and many-core GPUs. They support cross-platform operations and can be run on Windows, Linux, iOS, Android, etc. Available deep-learning toolkits are listed in Table 2.

Table 2. Summary of open-source deep learning toolkits with features

Toolkit	Developed by	Resealed Date	Features
TensorFlow [13, 14]	Google	November 2015	• TensorFlow gives the freedom and control to build complicated topologies using tools like the Model Subclassing API and Keras Functional API. • Efficiently handles multi-dimensional array-based mathematical formulas. • Support GPU and CPU architectures. • C++, Python languages are used.
Caffe [15, 16]	UC Berkeley	April 2017	• Provides a flexible and effective platform to build, train, and deploy deep neural networks. • Caffe is frequently employed in computer vision applications like image classification, object detection, and segmentation. It primarily focuses on CNNs. • C++ language used.
CNTK [17, 18]	Microsoft	January 2016	• Contains fundamental building blocks needed to build a neural network. • Implemented using C++ and Python but available in C# and Java.
PyTorch [19]	Facebook	February 2017	• Python-based PyTorch is thought to be particularly user-friendly. In this framework, code execution is relatively simple. • PyTorch makes use of all the features and services that the Python environment offers. • Users can rapidly change network behavior thanks to a feature called dynamic graph computation, which eliminates the need to wait for all the code to be executed. • C, C++, CUDA and Lua languages are used.
Theano [20, 21]	MILA, University of Montreal	2007	• Allows the efficient evaluation of mathematical operations, including multi-dimensional arrays. • Its primarily use for creating deep learning projects. • Works much more quickly on a graphics processing unit (GPU) as compared to a CPU. • Written in Python, CUDA

Table 2. Summary of open-source deep learning toolkits with features (continued)

Toolkit	Developed by	Resealed Date	Features
MXNet [22]	Apache	May 2022	• Allows a hybrid front-end smoothly switches between Gluon eager imperative mode and symbolic mode, to give flexibility and speed. • MXNet is extended by a robust community of tools and libraries that support use-cases in computer vision, NLP, time series, and other areas. • Deep integration with Python, and support for C++, R, Java, Julia, JavaScript, Scala, Go, Perl.
Keras [23]	MIT (2015)	March 2015	• Its customizable foundation allows it to run on both GPU and CPU. • Simple, scalable, and reliable API. • Supports almost all neural network models. • Written in Python.

3.3 Convolutional neural network-CNN

Convolutional neural networks, shortly CNNs, have become the most popular deep learning frameworks in recent years because of their unique features. Convolutional neural networks have a complex structure and usually include an input layer, a convolutional layer, a pooling layer, a fully connected layer, and then finally an output layer. The convolutional and pooling layers can be used more than once. Other layers, such as the batch normalization (BN) layer, the drop-out layer, and the activation layer can be used for various purposes to improve the performance of a model. The convolution layer performs convolution operation between the receptive field and the filter and continues this process for whole images. The pooling layer decreases the size of the feature map. Although CNN architectures are computationally expensive, their success rate in plant disease identification and recognition has raised the profiles of deep learning methods in the agricultural sector [24]. Analysis of state-of-the-art DL (CNN) architecture [25] is presented in Table 3.

Table 3. Analysis of state-of-the-art DL (CNN) architecture

Architecture	Year	Parameters	Salient Features
LeNet (LeNet-5) [26]	1998	60K	First and simple CNN that was able to classify the digit and was applied to recognize hand-written numbers on checks in the banks.
AlexNet [27]	2012	50 M	Considered as first modern CNN trained on more than a million images (ImageNet database). Achieved optimal performance using ReLu and dropout layer to solve overfitting.
OverFeat [28]	2013	145M	Performed classification, localization, and detection of objects in an image with a single CNN.
ZFNet [29]	2014	42.6M	Modified from AlexNet where filter sizes and stride of the convolutions are reduced, and accuracy is improved. Its major contribution is visualization of intermediate layers.
VGGNet [30]	2014	138.4M	It is a popular and widely used model because of its simplicity. VGG uses a 3*3 filter compared to AlxNet (11*11) and ZFNet (7*7).
GoogLeNet [31]	2014	7M	Fewer parameters than AlexNet. Winner of ILSVRC 2014.
ResNet [32]	2015	25.5M	Better than VGG and GoogLeNet in terms of accuracy. It solves the vanishing gradient problem.
Highway Networks [33]	2015	2.3 M	Multipath concepts were introduced.
SqeezeNet [34]	2016	1.25M	Fire modules are used to reduce the parameters. 50 times smaller model than VGG.

Table 3. Analysis of state-of-the-art DL (CNN) architecture (continued)

Architecture	Year	Parameters	Salient Features
DenseNet [35]	2017	7.2M	Uses dense connections between layers, through dense blocks.
Xception [36]	2017	22.9M	Depthwise separable convolution method used. Perform better than InceptionV3.
MobileNet [37]	2017	4.3M	It is faster as well as a smaller model that uses depth-wise separable convolution.
CBAM: Convolution block attention module [38]	2018	-	Provides intermediate feature maps. It can be smoothly integrated into any CNN architecture due to its lightweight and universal module, which incurs very little expense.
CBCNN: Channel Boosted CNN [39]	2018	-	Numbers of input channels increased to improve the capacity of the network.
EfficientNet [40]	2019	5.3 M	Its salient characteristic is its compound scaling mechanism, which consistently scales the depth, width, and resolution of the neural network.

3.4 Publicly available plant image datasets

To design and develop a vision-based system to classify and detect plant disease, large image datasets are required as they are used to train the deep-learning models. Datasets such as ImageNet, Pascal-Voc 2007/2012, and COCO, which are used for a variety of computer vision-based tasks, are not available for plant leaf disease recognition. For an automatic plant leaf disease detection system, the image datasets can be assembled by self-collection or from public datasets. In self-collected, images are often collected from the real field through aerial imaging, camera photography, vehicle robot, hyperspectral imaging, and so on. There are few public datasets available for leaf disease research. Some publicly available leaf and crop image datasets are listed in Table 4 with basic description.

Table 4. Descriptive analysis of public datasets of plant disease

Datasets	Crops	Description About Dataset	Link
PlantVillage	Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper Bell, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato	Total of 50,000 images of 14 crop varieties and 26 diseases	[41]
Data for: Identification of Plant Leaf Diseases Using a 9-layer Deep Convolutional Neural Network	14 Crops	In this dataset, 39 different classes of plant leaves and background images are available. This dataset contains 61,486 images; 39 different classes of plant leaf and background images are available. Six different augmentation techniques, image flipping, Gamma correction, noise injection, PCA color augmentation, rotation, and Scaling for increasing the dataset size are applied.	[42, 43]
New Plant Diseases Dataset	Same as PlantVillage	This dataset is recreated from the PlantVillage dataset. using offline augmentation which consists of about 87K RGB images.	[44]
PlantDoc [45]	Apple, Bell Pepper, Blue Berry, Cheery, Corn, Grape, Peach, Potato, Raspberry, Soyabean, Squash, Strawberry, and Tomato.	A total of 2,598 data points include 13 plant species and up to 17 classes of diseases.	[46]
Rice Leaf Diseases [47, 48]	Rice	Bacterial leaf blight, Brown spot, and Leaf smut, each having 40 images in .jpg format.	[49]
Embrapa/ Digipathos (PDDB) [50]	Soyabean, Citrus, Coconut tree, Dry bean, Cassava, Passion Fruit, Corn, Coffee, Cashew Tree, Grapevine, Oil Palm, Wheat, Sugarcane, Cotton, Black pepper, Cabbage, Melon, Rice, Pineapple, Papaya, and Cupuacu.	Total of 2326 images of 171 diseases and other disorders affecting 21 plant species	[51]
Plant Pathology 2020-FGVC7 [52]	Apple	3642 images are in this dataset divided into training and testing sets. All images are in jpg format.	[53]

Table 4. Descriptive analysis of public datasets of plant disease (continued)

Datasets	Crops	Description About Dataset	Link
OSF Dataset [54]	Maize (corn) leaves	The largest public dataset of 18,222 images taken in the field	[55]
Dataset for Crop Pest and Disease Detection [56]	Cashew, Cassava, maize, and Tomato	The dataset is presented in two folds; the raw images fold consists of 24,881 images (Cashew:6,549, Cassava: 7,508, Maize: 5,389, and Tomato: 5,435) and a fold of augmented images consisting of 102,976 images (Cashew: 25,811, Cassava: 26,330, Maize: 23,657 and Tomato: 27,178). Finally categorized into 22 classes.	[57]
APS image Database		This database contains nearly 7000 images.	[58]
RoCoLe [59]	Coffee	A total of 1560 images were acquired using a 5 MP smartphone camera in Ecuador.	[60]
Corn Disease and Severity (CD&S) Dataset [61]	Corn	The CD&S dataset consists of 4455 images where 2112 field images and 2343 augmented images.	[62]
Citrus fruits and leaves datasets [63]	Citrus	This dataset consists of 759 images, consisting in 150 fruit images and 609 leaf images.	[64]
Flavia Leaf dataset [65]	Leaves of 32 plants	This dataset contains 2621 images of 32 plants.	[66]

3.5 Image preprocessing

Image pre-processing, which brings the images into the standard and common format, is an essential step in a computer vision-based system [67]. Image pre-processing operations are performed at a low level of abstraction, which means the inputs and outputs of these operations are images only. Image quality can be degraded due to lighting effects, shadow, and weather conditions, and noise can be added to the images at the time of acquisition. Therefore, to improve image quality, and remove noise and complex backgrounds, image pre-processing must be applied. In the case of the above-mentioned problems, the image pre-processing steps must be applied, and if not applied, the performances of deep learning methods can be adversely affected [68]. Before being fed into the feature extractor layer of a deep learning model, input images are pre-processed to reduce the computational cost and increase the disease detection accuracy. Cropping, smoothing, color space conversion, original background elimination, and image enhancement are widely used, and the popular techniques are discussed in this literature review. Usually, color space conversion is used first, and other pre-processing methods follow [69]. HIS, RGB, L*a*b, HSV, YIQ, and grayscale color space conversion are widely used by various researchers [70-75]. Among the above-mentioned color space conversion methods, HSV and L*a*b are the most widely used [76-78].

After color space conversion, various filters and enhancement tools are applied to the images before feeding into deep learning models. Cropping is a useful technique to eliminate unwanted areas and complex backgrounds from the input images. Mean and median filters are used to remove noise from images [79]. To sharpen the image details, Gaussian and Laplacian filters are applied [80, 81]. Moreover, augmentation is a technique involving artificially increasing more data by applying various augmenting techniques to existing datasets [82]. Various image augmentation techniques like image flipping, gamma correction, scaling, noise addition, cropping, resize, zoom, rotation, random shift, affine transformation, brightness transformation, and contrast enhancement are applied for increasing the size of the dataset [83, 84].

3.6 Deep learning methods for plant disease detection and classification

Various deep learning-based plant disease classification and detection algorithms that have been implemented and tested in recent years are discussed and summarized. In the case of plant disease classification, it has been demonstrated that CNN transfer learning is more authentic than the scratch approach [84-86]. A summary of the comparative analysis of reviewed deep learning algorithms is shown in Table 5. According to Arun and Umamaheswari [87], a complete concatenated deep learning (CCDL) architecture was proposed, and it was composed of two parts: a feature extraction part and a classification part. In feature extraction, point convolution (PC) and standard convolution (SC) are used with the same padding where a complete concatenated block (CCB) has been applied as a core functional unit.

Thakur *et al*. [88] proposed a lightweight model called VGG-ICNN, which was designed by appending three blocks of GoogLeNet with the first four convolutional layers of VGG. Five publicly available datasets were used to train and evaluate the model's performance. The model gave classification results that varied from 90% to 99% on five different datasets. Algani *et al*. [89] proposed a deep learning-based method called ACO-CNN (Ant Colony Optimization with Convolution Neural Network) that was used for disease detection and classification. As image preprocessing for enhancement of leaf images, a median filter was used for reducing noise and removing other objects. The ACO-CNN model achieved a 99.98% accuracy rate, which indicated better performance than other deep learning methods. Bensaadi and Louchene [90] proposed a low-complexity CNN architecture to classify tomato leaf disease, which enabled prompt online classification. Fifty-seven thousand tomato leaf images, taken under a normal environment, were used to train the model. The model achieved 97.04% accuracy, which error of less than 0.2. Wang *et al*. [5] proposed a CNN-based tomato disease detection and segmentation model. Faster RCNN and Mask RCNN objection detection methods were combined with four CNN models, i.e., VGG16, ResNet-50, ResNet-101, and MobileNet. The Mask R-CNN model with ResNet-101 performed well and achieved high detection rates on all types of tomato diseases, with a mAP value of 99.64%. Although MobileNet required a shorter detection time, it was less accurate than ResNet-101. Singh *et al*. [91] used CNN AlexNet, which included 5 convolution layers and 3 Max-pooling layers. A maize leaf dataset was taken from the PlantVillage dataset and the whole dataset consisted of 2292 images of two different categories of diseases, leaf spot (gray leaf spot, Cercospora leaf spot), and common rust. The dataset was split into 60% for training and 40% for testing, and model was run with various numbers of iterations such as 25, 50, 75, and 100. Accuracy was observed throughout the process and increased with epochs. Chen *et al*. [92] proposed a grape leaf disease identification algorithm that had two parts: image segmentation and image classification. The first part included an enhanced artificial neural network (E-ANN) based algorithm for segmentation that extracted the disease spot accurately. The segmented images were then fed into a CNN architecture for classification. Their plan was to use this method in an embedded system to monitor and recognize plant diseases automatically. Bell and Dee [93] developed a plant image classification method where the Canny edge detector was used first for detecting edges and the edges were then classified into background edges or plant edges using a shallow CNN method. They further subclassified the edges into plant edge, leaf edge, and leaf-on-leaf edge or internal leaf noise. Finally, region-based segmentation was used for counting the leaves. *Arabidopsis thaliana* plant images were sampled from the Aberystwyth Leaf Evaluation Dataset (ALED) for this research. The difference in count (DiC), the absolute difference in count (|DiC|), the foreground/background dice (FBD), and the symmetric best dice (SBD) were calculated as metrics to measure the performance of the algorithm. Krishnan *et al*. [94] came up with a disease detection system for banana leaves where real filed photos were sampled from the CIAT image gallery and used. The overall quality of the image dataset was improved using various preprocessing techniques and then a hybrid segmentation, TGVFCMS (total generalized variation fuzzy c means) algorithm was applied for the segmentation of the disease area. For final classification, the segmented images were fed into a CNN model that was built up with convolution, ReLu, pooling, and fully connected layers. The proposed CNN with TGVFCMS outperformed with an accuracy of 93.45%, a sensitivity of 89.04%, and a specificity of 96.38%.

Table 5. DL-based methods used in plant disease classification and detection

Used DL Model	Description of Work	Utilized Dataset	Crop/ Leaves	Accuracy
CCDL [87]	Complete Concatenated Deep Learning (CCDL) architecture using Complete Concatenated Block (CCB) as a main unit.	PlantVillage	Multi Crop	Achieved classification accuracy of 98.14%
VGG-ICNN [88]	This model was designed by appending three blocks of GoogLeNet with the first four convolutional layers of VGG. Five publicly available datasets were used to train.	PlantVillage, Embrapa, Apple, Maize, and Rice Dataset	Multi Crop	Achieved 99.16% accuracy on PlantVillage Dataset.
ACO-CNN [89]	A deep learning-based technique, ACO-CNN (Ant Colony Optimization with Convolution Neural Network) was used for disease detection and classification.	Citrus fruits and leaves	Citrus leaves	Achieved a 99.98% accuracy rate.
CNN [90]	Low-complexity CNN model for classifying leaf disease.	Custom dataset	Tomato	Achieved 97.04% accuracy where the error is less than 0.2.
Faster RCNN and Mask RCNN [5]	Faster RCNN was used to classify tomato disease and Mask RCNN for detection and segmentation. Four deep CNN models: VGG16, ResNet-50, ResNet-101, and MobileNet combined with two object detection methods.	Images are collected from the internet.	Tomato	With Mask R-CNN, ResNet-101 shows highest detection rate, mAP=99.64%
AlexNet [91]	The proposed AlexNet architecture is used to detect leaf disease accurately.	PlantVillage	Maize leaf	Achieved 99.16% accuracy
Enhanced-ANN and CNN [92]	Enhanced ANN is used for image segmentation and then segmented images are fed into CNN for classification.	PlantVillage	Grape leaf	An average accuracy of 93.75% recall 100%
Shallow CNN and Canny edge detector [93]	First edge classification is performed and then region-based segmentation.	Aberystwyth Leaf Evaluation Dataset (ALED)	*Arabidopsis thaliana* plants	The difference in count (DiC), Absolute Difference in Count (|DiC|), Foreground/ Background Dice (FBD), and Symmetric Best Dice (SBD) were calculated.

Table 5. DL-based methods used in plant disease classification and detection (continued)

Used DL Model	Description of Work	Utilized Dataset	Crop/ Leaves	Accuracy
CNN with hybrid fuzzy C- means (2022) [94]	A hybrid segmentation, TGVFCMS, used for segmentation and then a CNN for classification.	Real field photo from CIAT's image library	Banana Leaf	Accuracy 93.45% Sensitivity 89.04% Specificity 96.38%
Plant AlexNet with Particle Swarm Optimization (PSO) (2022) [95]	AlexNet transfer learning was used for feature extraction from input images and features selected using PSO.	Real-field images datasets	Wheat, Cotton, Grape, Corn, and Cucumbers	Accuracy 98.83%, Specificity 98.56%, Sensitivity 98.78%, Precision 98.67%, and F-score 98.47%.
VGG16, GoogLeNet, InceptionV3 (2020) [96]	VGG16, GoogLeNet, and InceptionV3 CNN architectures were tested with transfer learning	PlantVillage, IPM, and Bing	Multiple crops Plants	98% top-1 accuracy by VGG16.
ResNet50 (2020) [97]	A pre-trained ResNet50 model was used with data augmentation to optimize the classification result.	PlantVillage	Tomato	Accuracy of 97%.
EfficientNet (2021) [98]	An efficientNet model was trained with transfer learning and training with the original and augmented dataset.	PlantVillage	Multiple plant (14 Species)	With original datasets, B5 and B4 models show 98.42% and 99.91% accuracy respectively. With an augmentation of the original dataset, the B5 and B4 models show 99.97% and 99.39% precision respectively.
ResNet and U-Net (2020) [99]	Proposed ResNet-based disease detection method and a model for disease severity estimator using modified U-Net.	PlantVillage	Tomato	When trained with the original color dataset, the classification accuracy was 0.970. With the background masked off, the classification accuracy dropped to 0.940.
3D-CNN (2018) [100]	Developed 3D CNN architecture	Real-field Hyperspectral images	Soyabean	Classification accuracy of 95.73% and an F1 score of 0.87 for the infected class.

AlexNet transfer learning with particle swarm optimization (PSO) was offered by Elaraby *et al*. [95] for plant disease classification and detection. AlexNet transfer learning was used for feature extraction from input images and features are selected using PSO. AlexNet used five convolutional layers, and the max-pooling layer was used after the first, second, and fifth convolutional layers. Activation function ReLu was used in the hidden layers and SoftMax in the output layer. The researchers used over 13,000 images of 5 various plants of 25 types of disease where the dataset was divided into training and test sets in an 80%: 20% manner. Lee *et al*. [96] investigated transfer learning; one was fine-tuning of an ImageNet pre-trained model (FTIN) and the other one was a fine-tuning of PlantCLEF2015 pre-trained model (FTPC). Pretrained CNN VGG16, GoogLeNet, and InceptionV3 architectures with different datasets namely PlantVillage, IPM, and Bing images, were used for training and testing. In a study by Kaushik *et al*. [97], a ResNet50 pre-trained model was trained with PlantVillage datasets to classify tomato diseases. Image augmentation was used to increase the dataset artificially by 4 times and a 97% accuracy was achieved. Atila *e al*. [98] worked with EfficientNet which had eight models, B0 to B7, for the classification of tomato leaf disease, and the results were compared with other deep learning models. Their proposed model used Swish as an activation function. PlantVillage datasets and their augmentations were used for training the models. With original datasets, the B5 and B4 models gave 98.42% and 99.91% accuracy, respectively. With augmentation of the original datasets, the B5 and B4 models showed 99.97% and 99.39% precision, respectively. Wspanialy and Moussa [99] proposed a disease detection system for tomato leaves using a ResNet-based deep learning model and was able to detect new instances of disease. They then proposed a method for measuring disease severity using modified U-Net architecture. They used the PlantVillage dataset. When trained with the original color dataset, the classification accuracy was 97%. With background masking off, the classification accuracy dropped to 94%. Nagasubramanian *et al*. [100] proposed a 3D-CNN model for soybean charcoal rot disease identification. Hyperspectral images were used in this research. The images were captured at 240 different wavelengths. Their proposed model achieved a classification accuracy of 95.73% and an F1 score of 0.87 for the infected class. Das and Rupa [101] and Das [102] examined the potential of transfer learning (TL) of CNN in leaf disease classification.

4. Challenges in Using Deep Learning in Disease Detection

In the above-discussed sections, the feasibility of using various deep learning methods in plant leaves and crops diseases detection and classification was assessed and summarized. From this conducted literature review, it is obvious that deep learning-based methods have great potential and play an influential role in plant leaves and crop disease detection and classification. However, there are some challenges that restrict and sometimes degrade the performance of the models. The research community around the world needs to consider and focus on those challenges to mitigate the adverse effects on performance. Challenges encountered at the time of the literature study are described below.

4.1 Size and number of datasets

From the literature review, there are very few datasets available, and for some plants, there are no publicly available datasets. Moreover, the size of publicly available datasets is very small, which is very crucial for disease detection and classification using deep learning. Building a new data set is very difficult as it involves a series of relevant tasks. Deep learning-based plant leaf and crop disease detection and classification systems require a significant number of image samples for model training. Without enough data samples for training, the deep learning method does not work well, and the model performance is eventually degraded. Non-uniform and imbalanced training datasets also produce bias DL models. Therefore, each class in the datasets should have approximately the same number of images to ensure optimized performance accuracy of DL architectures. The use of small image datasets for training has several unfavorable effects, which continue to hinder the successful spread of deep learning technology even when the technical barriers to automatic plant disease classification have been largely overcome [103]. So, it is extremely true in the case of deep learning that "More data in training the model ensures optimal performance".

4.2 Image acquisition

It was noticed throughout the literature study that the accuracy or experimental outcome of deep learning methods in plant disease detection and classification is vastly affected by the type of dataset utilized in research, namely, real-field images or laboratory-controlled images. In the most publicly available datasets, images are laboratory-conditioned images. However, real-field image datasets are more important for developing real-time disease detection and classification systems. While capturing images for datasets, it is vital to take photos from various viewpoints, at different times, and under different environmental conditions, actions which not only increase the volume of image datasets but also boost the accuracy of the deep learning process [104]. Additionally, image capturing modalities also have a greater influence on the performance of deep learning-based systems. Therefore, the disease prediction capacity of deep learning can be affected by several factors, including choice of imaging devices, environmental conditions, time of photography, viewpoint selection and so on.

4.3 Concurrent multiple diseases

Deep learning-based plant disease detection and classification methods usually operate on the basis of only one disease symptom per image. However, in real-field scenarios, multiple diseases can be present in the same image, and various nutritional insufficiencies and pests can also be present [104]. So, only one disease is classified or detected while others remain undiagnosed.

4.4 Various diseases with the same symptoms

There are different plant leaf and crop diseases that produce the same patterns and symptoms that make the classification and detection task more challenging. In a deep learning-based system, it is designed for a specific disease, which is identified correctly while others are difficult to recognize. This type of problem can also create a hazardous situation in dataset annotations.

4.5 Detection accuracy and speed

Deep learning-based plant disease detection methods ensure better performances than other traditional image processing and machine learning algorithms, but deep learning-based systems have higher computational costs. To get the optimized detection speed or guaranteed prediction accuracy, deep learning models need to be trained with enough images and require learning all features from the images, which increases the computational cost and eventually the prediction time. In order to secure speedy detection, it is compulsory to lessen the number of calculations. So, it is crucial to develop methods with considerable accuracy and speed.

5. Conclusions

In this review, an in-depth study was carried out, summarized and compared various DL-based approaches to plant disease classification and detection. The flawless classification and recognition of plant diseases are key steps in sustainable agricultural farming. Precise manual management of plant diseases in terms of detection and classification is difficult because these traditional methods involve huge amounts of time, cost, manpower, expertise, and so on. Along with those factors, different plant diseases have similar symptoms and disease patterns, and it is extremely challenging for farmers to detect diseases accurately with their bare eyes. Various problems with traditional image processing and machine learning methods are tried to be addressed and resolved by using deep learning-based methods.

Based on the literature reviews, there were numerous ways to improve the overall prediction accuracy of DL-based plant disease detection systems. Transfer learning is one such way that is used vastly in plant leaf disease detection systems. Transfer learning allows researchers to use existing DL models directly, without developing them from scratch, and improve accuracy. Another example is the use of larger datasets to boost prediction accuracy because models trained on huge datasets eventually learn more prominent features automatically. However, a larger image dataset increases storage and computational costs. Much remarkable development was noticed with the DL method, especially CNN, in plant disease classification and detection, during the last few years. However, there are still some gaps or problems in the research that need to be solved, which are listed below:

- An in-depth study is essential to figure out all the limitations or research gaps of deep learning-based methods for plant disease detection and classification. Also, a recognition of the factors that affect the performance accuracy of existing DL methods is needed.
- The PlantVillage dataset has been used by most researchers in plant and crop disease detection and classification with deep learning-based systems. The images in the dataset have a simple background, and that is why the DL model trained with this dataset does not perform well on real field images with compound backgrounds. To make the DL models more robust and practical, real-field images with complex backgrounds should be considered.
- Along with the identification and categorization of plant diseases, measurement of the severity of plant leaves and crops disease is equally important for agricultural farming. Future researche should focus on how DL methods can be used to measure disease severity because the severity of the disease changes over time and is directly related to overall loss.

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