SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V11I9P116

Volume 11 Issue 9, 174-191, September 2024

Review Article

Current Developments in Crop Disease Identification Using Computer Vision: A Critical Review of Related Works and Techniques

Anandraddi Naduvinamani[1], Jayshri Rudagi[2], Mallikarjun Anandhalli[3]

[1,2]*Electronics and Communication Department, S.G.Balekundri Institute of Technology Belagavi, Karnataka, India. Affiliated to Visveswaraya Technological University (VTU) Belagavi, Karnataka, India.*
[3]*Department of Electronics and Communication Engineering, Central University of Karnataka Kalburgi, India.*

[1]*Corresponding Author : anandreddi02@gmail.com*

Received: 06 July 2024 Revised: 16 August 2024 Accepted: 07 September 2024 Published: 30 September 2024

Abstract *- Computer vision and especially deep learning play a pivotal role in the recognition of patterns in diverse kinds of images. Recent years have seen increased attention from both academic and business communities for autonomous learning in this field. Deep Learning (DL) based strategies have found much usage in areas like NLP, speech recognition, and video analysis. At the same time, it has become a centre of attraction for scientists studying methods for agricultural plant protection, such as pest spread assessments or the identification of plant diseases. Researchers may avoid the pitfalls of selecting disease spot qualities subjectively, derive more accurate plant disease features, and speed up the rate of technological transformation, all by disease detection in plants using deep learning. In this study, we will take a look at how far the DL mechanism has come in the arena of detecting ailments in crop leaves during the past few years. In this article, we converse about the cutting-edge progressions in the automatic diagnosis of leaf diseases, utilizing both deep learning and standard image processing methods, as well as highlight the obstacles that must be overcome.*

Keywords *- Deep Learning (DL), Natural language processing, Disease spot qualities, Identification of plant diseases.*

1. Introduction

Being amongst the world's largest sectors, farming offers immense support in the forms of food, income, and employment. Since there are so many farmers in India and other low and middle-income nations, agriculture accounts for 18% of national income and 53% of total employment [1]. Over the previous three years, agriculture's share of the nation's Gross Value Added (GVA) has climbed from 17.6% to 20.2% [2, 3]. The majority share of the expansion of the economy could be accredited to agriculture. Therefore, the quality of food production could be negatively impacted if plant diseases and insect infections affect agriculture. This growth in population led to an increase in the demand for nutrients. Increasing agricultural output and ensuring crop security are essential to meeting this urgent demand. However, a wide variety of pathogens in crops' natural habitats makes them susceptible to a varied range of ailments. Disease-causing microorganisms include viruses, fungi, bacteria, and others [1]. The quantity and quality of food produced might suffer greatly when crop diseases lower output by as much as 95% [2]. In order to prevent massive losses and cut down on the overuse of potentially dangerous pesticides, early disease detection is essential. Small farmers and those in underdeveloped nations sometimes rely solely on visual symptoms to diagnose crop illnesses. This is a laborious job that calls for knowledge of plant pathology and extensive time for treatment [3]. Additionally, if a peculiar disease is attacking the field, farmers try to get expert assistance to find an accurate and effective diagnosis, which certainly leads to higher treatment expenses [4]. Therefore, huge farms cannot rely on visual inspection, and it can even lead to inaccurate projections because of human error [5]. As consumer demand rises, businesses must find ways to reduce the harmful effects of chemical intake on the environment and human health. Researchers have developed technological recommendations for the early detection of crops in an accurate, quick, and secure manner [78].

Several approaches [6-9] have been put forth with the aim of automating the detection of diseases. Both direct and indirect approaches are established for the automated detection of diseases in the crops [10]. Direct methods include molecular [74] and serological [74, 75] methods, which allow for precise pathogen identification causing the ailment but take a long time to collect, process, and analyze the samples. In contrast, indirect methods, like optical imaging techniques [76], can detect illnesses and forecast crop health by analyzing variables, including changes in morphology and rate of breathing out. Two of the most common indirect techniques for early illness detection include fluorescence and hyper spectral imaging [77]. However, low-income farmers sometimes have a hard time obtaining hyper spectral devices due to their high cost, cumbersome size, and limited availability, despite the fact that hyper spectral photographs are a vital source of information because they provide more details than standard images do [17]. There are many other digital cameras available at reasonable costs in retailers like Best Buy and Amazon. So far, most automatic identification methods have handled images in the visible domain, where very precise and quick techniques can be applied.

Visual crop inspection can be a useful tool for assessing quality, but it usually is time-consuming, expensive, and imprecise. Researchers have developed a number of methods, such as those used in object recognition and image analysis for quality control purposes. In order to identify and categorize agricultural diseases [1-3], this paper uses image processing technology. High-resolution images, which are notoriously difficult to get, are essential for this image processing method's identification and categorization of illnesses. Because of this, disease prediction is not only difficult but also time-consuming. The most commonly used of conventional crop disease detection methods, manual observation, has been shown to be ineffective and unreliable. Due to a lack of professional expertise, farmers and the limited availability of agricultural professionals they often fail to take preventative measures until it is too late. In the last few years, many advancements have been made in various fields, including computerised pattern recognition [1], image processing techniques [2], computer vision [3], and others. Using computers to automatically identify diseases is a useful step in solving agricultural problems.

Image pre-processing, researcher-designed complicated disease characteristics regarding feature extraction [5], and methods for Machine Learning (ML) [6] for identifying plant illnesses constitute the three pillars of the conventional machine vision [4] approach to detecting diseases in crop leaves. Many different supervised machine learning classification methods, including NB [5], KNN, DT, SVM, and RF [81], are discussed for identifying and classifying diseases from plant leaves, and a comparison is done between them. Additionally, it offers a variety of methods that, when compared to others, produce the most precise results. Several domains [12] benefit from the use of these classification strategies, including biological signal processing [13] and healthcare [14, 15].

Improvements in plant disease recognition research have been made thanks to the application of DL's latest advancements in technology. Since Deep Learning (DL) technology is hidden from the end user, researchers in plant protection and statistics do not need to have a high level of expertise to use it. With DL, researchers recognize and label plant disease areas based on photo characteristics, saving time and effort over manual processes. For these reasons, the application of DL to the problem of plant disease recognition has recently been a focal point of scientific inquiry. Larger datasets, flexible multicore GPUs, and Developments in deep neural network training, as well as supporting software libraries like CUDA from NVIDIA are all important factors.

1.1. Research Gap and Problem Statement

Despite significant advancements in plant disease detection using ML and DL technologies, there remain substantial challenges in making these systems widely accessible and effective for smallholder farmers, particularly in low- and middle-income countries. Most current disease detection techniques rely on high-resolution imaging, expensive equipment, and complex computational processes that are often unavailable or too costly for small-scale farmers. Moreover, traditional ML methods like NB, KNN, DT, and RF have been used for classification, but their accuracy may be limited in identifying subtle disease patterns, especially when applied to diverse plant species and varied environmental conditions. In addition, hyperspectral imaging, though highly accurate, is not a feasible solution for farmers due to its high cost and operational complexity. While DL has emerged as a more automated and less expertise-dependent approach, its reliance on large datasets, high computational power, and sophisticated GPUs limits its practical implementation in resource-constrained settings. The current approaches to automated plant disease detection, while promising, are not scalable or cost-effective for smallholder farmers in low-income regions. These methods require expensive tools, complex processing techniques, or large datasets, which hinder their adoption in real-world agricultural practices. As the global demand for food continues to rise, there is an urgent need for an accessible, efficient, and accurate system that can provide early disease detection to reduce crop losses without reliance on costly technologies or expert knowledge. Developing a lightweight, low-cost solution that leverages advances in image processing and DL while being adaptable to resource-constrained environments is essential to improving agricultural productivity and crop security globally.

2. Crop Disease and their Symptoms

This section discusses the numerous methods used to diagnose plant illnesses, lays out a taxonomy of those diseases, and explains what image processing and machine learning are. It also shows how hyper spectral images, the IoT, DL, and transfer learning may be used for disease diagnosis. The disease's symptoms, which include stunted crop growth, are readily apparent. The first sign of disease in plants is a change in leaf colour. In addition, the structure and feel of the leaves can tell a lot about the presence and severity of a disease. Thus, leaf photos can be processed to detect illnesses like mildew, rust, and powdery mildew [26, 27].

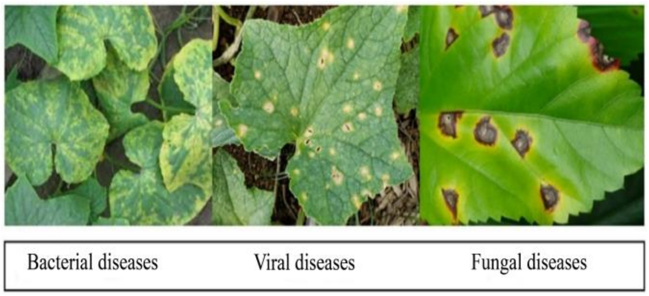

Fig. 1 Broad categorisation of plant diseases

Below is a quick discussion of the three kinds of plant diseases [28] that are depicted in Figure 1 and listed in Table 1.

- Virus diseases [1]: Infectious plant illnesses are particularly challenging to diagnose since there is no reliable signal that can be used to track their progression over time. As a result, their symptoms are often misinterpreted as indications of nutritional inadequacy or injury. Cucumber crawling bugs, aphids, whiteflies, and leafhoppers are all vectors for virus transmission.
- Fungal diseases [1]: Infectious fungi are to blame for a wide variety of foliar diseases, including downy mildew, anthracnose, and powdery mildew.

Table 1. Plant disease categories and features

Plant Leaf	Disease	Signs and symptoms	Category of Pathogens
Citrus	-Melanose -Greasy spot -Canker	-The leaf gets abrasive to feel while touching -Pale-to-brown blisters - Includes rounded to uneven, flattened, puffy, cracked, and sunken areas.	-Fungi -Fungi -Fungi, bacterial
Maize	Stalk rot	dull green leaf colour with the stem's bottom portions becoming yellow	-Fungi
Rice	Brown spot Blast leaf	- Centre is whitish-gray. - Patches of dark brown spot	-Fungi
Tomato	- Powdery mildew -late blight and early blight -Curl of yellow	-Yellow ring around the dark area - Dark area expands fast -Curly, yellowish leaf -A yellow halo around it when soaked in water	-Fungi -Fungi -Fungi -Virus
Wheat	-Rust -Powdery mildew -Bacterial blight	- Pale leaf stains -A grey or brown patch - has a green with yellow undertones halo	-Fungi -Fungi -Bacterial
Watermelon	- Downey mildew and anthracnose	- Uneven yellow spots with yellow to white dots	-fungi

- Bacterial diseases [1]: Vegetables are extremely susceptible to pathogen-caused illnesses. They gain access to the plant life indirectly, through cracks or holes. Insects, diseases, and even the tools used to perform routine agricultural chores like harvesting and trimming can cause damage to crops.

3. Research Questions

The driving force behind writing this paper is to identify standard and recent ML / DL approaches currently used for disease detection in crops. In addition, it seeks to identify the latest and cutting-edge machine learning methods that were implemented in the past. This leads us to our primary study topic, which is:

PRQ: “What cutting-edge machine learning techniques are applied to the problem of agricultural disease detection? To assist in refining the focus of the original research topic, a set of secondary questions is also provided:

SRQ2: Which crop diseases cause the most damage and are most common?

SRQ3: What kinds of data sets are there to choose from?

SRQ4: How do crop disease detection experts often measure success?

SRQ5: What are the most popular machine learning frameworks?

4. Deep Learning and Machine Learning for Classifying Plant Diseases

In the area of image processing, convolutional neural networks have demonstrated remarkable success as feature classifiers and extractors during the past decade. While this idea has been effectively implemented elsewhere, it is just recently making its way into the agricultural sector. This section provides a high-level summary of the various applications of ML in plant disease categorization, including the identification of weeds and weed infestations, the counting of flowers and fruits, and the grading of harvested produce.

Since 2015, DL has seen extensive use in the field of diagnosing leaf diseases. DL representation strategy that, rather than focusing on representing semantic aspects, tries to represent data optimization approaches optimally. Features are extracted automatically as opposed to manually as a result of the learning process. Also, DL is a part of the cutting-edge farming practices that will help the food business develop in areas like automation, advertising, massive amounts of data, pest control, healthcare diagnosis, and technology.

Ramesh et al. [1] produced data sets for use with Random Forest to determine which leaves were healthy and which were infected. In order to categorize images of both healthy and sick leaves, Training data sets for both kinds of leaves are used to train a random forest classifier. Researchers employed the Histogram of an Oriented Gradient (HOG) to choose certain picture attributes.

Harakannanavar et al. [2] assessed the affected tomato leaf samples. These tomato leaves disorder samples will help farmers detect diseases early and protect their crops. The correct diagnosis and categorization of these illnesses are essential. Tomato harvests can be impacted by a number of different illnesses. If these illnesses could be detected sooner, they could have less of an impact on tomato plants, leading to a higher crop output. Many novel approaches have been explored to identify and categorize various diseases. This project aims to assist farmers in accurately diagnosing illnesses in their early stages. To successfully characterize and categorize tomato illnesses, the CNN is utilized. The input photos are first subjected to preprocessing, during which the desired regions are extracted from the full-resolution versions. Second, the photos are processed further by playing around with different CNN model hyper-parameters. Ultimately, CNN can extract more elements from photos, including edge, texture, colour, and more.

Chug et al. [3] presented a revolutionary model that merges the benefits of ML and DL. Forty Hybrid DL models are included in the suggested framework. These models are a combination of eight built-in deep learning framework variants (EfficientNet B0-B7) used as feature extractors.

An approach for creating a hyper-plane that separates a problem space into several classes is called a Support Vector Machine (SVM). By increasing the distance between the closest-spaced data points in each category and the hyper-plane, SVM determines which hyper-plane is optimal for data separation. The kernel trick approach allows SVM to also work well with non-linear data. A function called the SVM kernel transfers input data from a low-dimensional space to a higher-dimensional space that is linearly separable. That explains why SVMs excel in high dimensional areas. Another popular use of SVM is in regression problems [29, 39]. Furthermore, in order to anticipate the incidence of powdery mildew on tomato plants, Bhatia et al. [79] presented a hybrid application of SVM by merging it with a logistic regression technique. A comparison study of several regression and classification techniques is presented in Table 2.

Table 2. Comparative analysis of classification/regression method

<table>
<tr><th>Article</th><th>Classification/ Regression</th><th>Kernel</th><th>Result</th></tr>
<tr><td rowspan="2">[19]</td><td rowspan="2">Classification</td><td>Polynomial</td><td>Acc=90%</td></tr>
<tr><td>Radial Basis function</td><td>Acc=97.4%</td></tr>
<tr><td>[20]</td><td>Regression</td><td>Linear</td><td>$r^2 = 0.45$</td></tr>
<tr><td>[21]</td><td>Classification</td><td>Linear</td><td>Acc=90%</td></tr>
<tr><td rowspan="5">[22]</td><td rowspan="5">Classification</td><td>Radial Basis Function</td><td>Acc=90.5%</td></tr>
<tr><td>Quadratic</td><td>Acc=92%</td></tr>
<tr><td>Linear</td><td rowspan="3">Acc=91%</td></tr>
<tr><td>MultiLayer perceptron</td></tr>
<tr><td>Polynomial</td></tr>
<tr><td>[23]</td><td>Classification</td><td>NA</td><td>Acc=94.6</td></tr>
</table>

Saleem et al. [4] implemented the NZDLPlantDisease-v1 dataset. For the identification of crop disease by making use of a recently generated dataset, the Region-based Fully Convolutional Network (RFCN), the best-attained DL model, has been improved upon. The data augmentation methods were assessed one by one once the optimal DL model was determined. After that, they looked into the results of DL optimizers, batch normalizers, weight initializers, and image resizers using interpolators. Subsequently, anchor box settings and position-sensitive score correlates were empirically observed to enhance performance. To further illustrate the applicability of the recommended approach, testing on an external dataset and a layered k-fold cross-validation procedure were employed.

Nandhini et al. [5] applied CNN and RNN to agricultural disease categorization and detection, adding to their already impressive track record of success in other areas. Their research focuses on developing a DL based framework for early prediction and disease classification to support plantain tree producers. Combining RNN with CNN, a novel progressive picture classification model for illness detection is proposed: the Gated-Recurrent Convolutional Neural Network (G-RecConNN). Plant picture sequences were utilised as inputs for the proposed model.

Arun et al. [6] offered a multi-crop disease detection model that uses the Complete Concatenated Deep Learning (CCDL) architecture to classify agricultural illnesses across crop kinds. Complete Concatenated Blocks (CCBs) were presented as fundamental building blocks in their design. To limit the total number of model parameters, the point convolution layer was placed at the beginning of each convolution layer in this component. The CCB's convolution layers are subjected to a full concatenation path. It improves feature map use and, hence, classification accuracy. The restructured Plant Village dataset was used for training the suggested framework. Pruned Complete Concatenated Deep Learning (PCCDL) models are trained models that have been reduced in size through pruning.

Chen et al. [7] improved the model's capability to detect subtle plant lesion traits by discussing DL techniques and developing a convolutional mixed network. To better plant disease recognition, they combined three lightweight Convolutional Neural Networks (CNNs) using ensemble learning to create a new network they named Es-MbNet. Model training opted for a two-stage approach based on transfer learning, focusing on the setup of network weights. To acquire the best possible model parameters, the network was retrained using the target dataset in the second training phase, utilising the weights learned in the first training phase. The comparative comparison of several machine learning methods is shown in Table 3.

Table 3. Comparison analysis of ML algorithms

Ref	Contribution	Dataset	Performance
[1]	HoG based feature extraction and classified by Random Forest classifier.	Custom/ Manually collected dataset	LR= 65.33 SVM= 40.33 KNN =66.76 CART= 64.66 RF= 70.14 NB =57.61
[2]	Equalisation of histograms and K-means clustering, DWT, PCA and GLCM features, SVM, CNN and KNN classifiers are used.	Tomato leaves	K-NN (97%) and CNN (99.6%), SVM=88%
[3]	Combination of machine and deep learning for classification and feature extraction, respectively.	IARI-TomEBD, PlantVillage-TomEBD and PlantVillage-BBLS.	Accuracy range =87.55–100% for IARI-TomEBD dataset
[4]	Optimized region-based fully convolutional network (RFCN)	NZDLPlantDisease-v1	Mean average precision =93.80%
[5]	G-RecConNN, or Gated-Recurrent Convolutional Neural Network, is a hybrid CNN and RNN model.	banana disease image dataset	NA
[6]	Complete Concatenated Deep Learning (CCDL), which uses point convolution and convolution layer.	Plant Village dataset	Accuracy = 98.14 %
[7]	Ensemble DL model by combining lightweight CNNs	Plant Village dataset	Accuracy =99.61 (local dataset) Accuracy =99.61% (Plant Village dataset)
[8]	DL architecture with inception land residual connection with depthwise separable convolution	Plant village, rice and cassava	Plantvillage dataset = 99.39%, rice disease = 99.66%, cassava dataset = 76.59%
[9]	VGG architecture combined with CNN	PlantVillage and Embrapa	PlantVillage =99.16%
[10]	Ant colony optimization with CNN	Custom dataset with greening, Canker, melanosis, and blackspots diseases	Accuracy=99.98% Precision=99.6% Recall=99.6% F1-score=99.99%

Table 3 provides a summary of research conducted in the agricultural sector using SVM as the ML model. It is possible to see the SVM type, kernel, and output. Most applications of SVM-based classification and regression algorithms in agricultural settings make use of linear, polynomial, or RBF kernels.

Hassan et al. [8] suggested a variety of DL based models for use in diagnosing crop diseases. However, DL models call for many parameters, making the training period longer and the implementation tricky on mobile devices. A fresh approach to deep learning utilizing the inception layer and residual connection has been suggested. One method for doing this is by employing depth-separable convolution.

Thakur et al. [9] presented the 'VGG-ICNN', a light weight CNN model, designed to detect crop illnesses from photographs of plant leaves.

Abd Algani et al. [10] used a novel DL approach called Ant Colony Optimization with CNN to identify and categorize diseases. ACO was used to study how well it could detect diseases in plant leaves. Images of plants had their color, texture, and leaf arrangement removed by a CNN classifier.

Pandian et al. [11] developed a unique Deep CNN model for identifying 42 leaf diseases across 16 plant species. They optimized the hyperparameters and added more data to the disease detection model to boost its accuracy. Using BIM, DCGAN, and NST, they were able to create augmented photos of leaves. In order to train the DCNN model, 58 classes of sick and healthy plant leaves were used. To find the best settings for the most often used hyperparameters, an arbitrary search was done by the coarse to fine method. Finally, the suggested DCNN's performance was compared to that of industry standard transfer learning methods. Table 4 presents the comparative investigation of various DL methods.

Table 4. Comparative analysis of different deep learning methods

Ref	Contribution	Dataset	Performance
[11]	Augmented and hyperparameter optimized Deep CNN	Custom dataset with 42 leaf diseases from 16 different plant species	Accuracy = 99.9655%, Avg. PR =99.7999%, Recall =99.7966%, and F1 =99.7968%.
[12]	Pre-trained Efficient DenseNet 201 and reweighted cross entropy loss function	Plant village and custom potato leaf diseases	Accuracy = 97.2%
[13]	Yolov5 as base architecture with new bottleneck and SE module for channel features	Custom dataset from rubber plantation	Precision for powdery mildew= 86.5% and Precision for anthracnose detection =86.8%
[14]	CNN with different augmentation strategies	Cucumber leaf infections caused by yellow spot viruses and zucchini yellow mosaic	Accuracy (%)=94.9, Sensitivity for MYSV (%)=96.3 Sensitivity for ZYMV (%)=89.5 Specificity (%)=97.0
[16]	DL using quicker region-based CNNs and a single shot multi-box detector	Apple leaves	mAP= 78.80%
[18]	RPN based two stage CNN	Citrus dataset from the Kaggle website	Accuracy =94.37% Average precision = 95.8%.
[29]	Entropy-ELM-based DL which uses pretrained : DenseNet201, ResNet101, ResNet50, and VGG16	A scan dataset for cucumber leaf diseases	Accuracy = 98.4%
[30]	Combined model by using SegNet, UNet, and DeepLabV3+ architectures at different stages	Corn leaves	mwIoU=0.8063 mBFScore= 0.8063

Mahum et al. [12] created a method utilizing a refined deep learning algorithm to categorize potato leaves into five distinct groups based on their visual characteristics. Using a pre-existing dataset, the model that was suggested is trained (called "The Plant Village") that contains photos of potato leaves labeled as Healthy, Normal, or Infected with Early Blight (EB) or Late Blight (LB), respectively. To speed up the process of disease classification in potato leaves, a pre-trained Efficient DenseNet model has been used, with the help of an additional transition layer in DenseNet-201. Since the training data is very unbalanced, their proposed technique benefits from the use of the reweighted cross-entropy loss function. Overfitting is kept to a minimum in the training of tiny training sets of potato leaves because of the thick relationships with regularization power.

Chen et al. [13] implemented a more effective crop disease identification model using the YOLOv5 network baseline. To begin, they employed a brand-new Involution Bottleneck module to cut down on parameters and calculations while simultaneously picking up spatial information at great distances. Second, a SE module was integrated to elevate the model's responsiveness to channel characteristics. To prevent the degeneration of the loss function “Generalized Intersection over Union” into “Intersection over Union,” “Efficient Intersection over Union” was introduced. The proposed strategies were implemented to enhance the network model's target recognition performance.

Kawasaki et al. [14] addressed illness detection in cucumber leaves caused by viruses like Zucchini yellow mosaic and yellow spot using a unique CNN architecture. They demonstrated that adding more data to the mix is more helpful in recognizing performance than simply adding more training epochs. Additionally, they dealt with numerous augmentation procedures across a variety of topologies to boost classification accuracy.

Durmus al. [15] showed the work carried out by training AlexNet and CNNs on SqueezeNet on the Nvidia Jetson platform to propose an expanded work. Alexnet's accuracy is slightly lower than that of projects where a TITAN X GPU was employed, but this is still quite respectable. In addition, the findings suggested that real-time experiments on crop disease detection systems are feasible. They demonstrated great performance in embedded applications and transferred the model to the embedded device for use in actual use.

Jiang et al. [16] introduced an alternate method of using DL in object detectors. In addition, the zone harboring diseases is classified and located using the features inside the bounding box using faster region based CNNs architectures and Single Shot Multi-box detector.

Barbedo et al. [17] indicated that images of discrete spots and lesions, rather than complete leaves, are needed for DL-based leaf disease classification. However, there are still open questions regarding the precision with which photos can be automatically segmented into individual lesions after the background has been removed. In addition, the mobile phone-based detection system for plant diseases uses a compact deep CNN technology. Additionally, the CNN model can be implemented on a mobile device, increasing the usefulness and accessibility of this technology to farmers.

Rahman et al. [18] used a two-fold deep CNN architecture to categorise citrus illnesses from leaf pictures and detect plant problems. A region suggestion network is used in the first stage to suggest probable target diseased areas, and a classifier is used in the second stage to assign the most likely aim area to the associated disease class.

Gehlot et al. [28] developed the EffiNet-TS design, which is an EfficientNetV2 Teacher or Student architecture consisting of the EffiNet-Teacher classifier, Decoder, and EffiNet-Student classifier. Since it feeds and employs a substantial portion of a country's population, agriculture is essential to national prosperity. One of the most difficult aspects of increasing farmers' revenue is the presence of plant diseases. Recent advances in deep learning have allowed for the development of highly accurate and efficient categorization frameworks, such as efficientNet, which has significantly expanded CNN's utility.

Khan et al. [29] suggested a deep learning system based on the Entropy ELM to diagnose diseases in cucumber leaves. The proposed system is used to train one of four pre-trained deep models with the goal of improving accuracy. Next, the Entropy-Elm method is applied to this model in order to pick the most useful characteristics. The opposite phase, which involves combining features from all pretrained models, is where the feature selection method comes into play. In the end, they did classification using a combination of features from the first two steps. The suggested framework was evaluated on a dataset of modified cucumber leaves, and it achieved an accuracy of 97.98%.

Divyanth et al. [30] utilized SegNet, UNet, and DeepLabV3+, three semantic segmentation models, in a two-step process. In the first phase, the complex backdrop is separated from the leaf image so that it may be detected in the second. After evaluating the performance of each segmentation model, they concluded that UNet was superior for stage one and that the DeepLabV3+ model was superior for stage two. They also enhanced previous methods of assessing the extent of disease by measuring the area of disease lesions. Nandi et al. [31] implemented the VGG-16, GoogleNet, ResNet-18, MobileNet-v2, and Efficient Net CNN models. They tried applying model quantization approaches to those three aforementioned CNN models and discovered that GoogleNet was the most accurate and had the smallest footprint. After quantization, the Efficient Net model reached 99% accuracy with a manageable size.

Table

Article	Real-world application	ML/DL Model	Model Parameters	Advantages/ Limitations
[10]	Real-time images of greening, Canker, melanosis, and blackspots diseases	Ant colony optimization with CNN	NA	Relies on optimization, which can lead to an increase in the time complexity.
[32]	Basal Stem Rot for hyperspectral images	Mask RCNN and VGGNet	Epochs=12 for VGG and 3000 for mask-RCNN	It is not experimented in realistic environments and can be extended towards non-normal bands.
[34]	Tomato disease detection	Generative Adversarial Learning	Adam Loss function = category cross entropy = Optimizer 32 is the batch size.	It is performed on a limited dataset where overfitting can decrease the system performance; however, data augmentation methods are added to minimize the overfitting.
[35]	Tomato disease detection	Inception ResNet V2 and Inception V3	32-batch, 15-Epoch batch size Acquiring knowledge = 0.01 and 0.00001	Reported high accuracy for 50% dropout; however, it is performed on a limited dataset.
[36]	Realt-time images, along with the plant village dataset	Pre-trained DL architectures for Transfer learning=InceptionV3, ResNet50, VGG16, DesneNet169, and Xception	Epochs= 100 Batch size =16	This approach has been reported to have the ability to generalize disease detection; therefore, it can be used for real-time deployable devices.
[37]	Tomato plant diseases (10 categories)	MobileNetV3Small, EfficientNetV2L, InceptionV3 and MobileNetV2	0.0001 is the learning rate. Batch Size: 4 Optimizer: Adam	It uses the PSO model for fine-tuning the parameters, which requires a customized objective function; thus, the optimization completely relies on it. PSO may result in poor convergence, resulting in estimating inappropriate parameters
[38]	Plant disease detection for paddy and tomato leaves	MobileNet DL model and KMeans clustering as ML model	Learning rate =0.01, 0.001 Train-test ratio=90-10 and 80-20	Works for limited datasets and is difficult to generalize for different datasets as it was trained on limited images

Algani et al. [10] utilized a CNN optimized with ants (ACO-CNN). Accuracy, precision, recall, and F1-score were all better for the ACOCNN model than for the C-GAN, CNN, and SGD models. C-GAN has an accuracy of 99.59%, CNN of 99.89%, and SGD of 85%. With an accuracy of 99.98%, the ACOCNN model has the highest F1 score of any currently available model. The identification of Basal Stem Rot was a primary focus of Yong et al.'s [32] research. They discussed deep learning and hyper spectral imaging. In this method, they analyzed spectral changes across leaf positions by segmenting the top-down image of the seedling into areas. To assess the role of the setting of images on identification accuracy, they segmented photos of the plant and fed them into a Mask RCNN. They used VGG16 and Mask RCNN to train their system, with VGG16 yielding the highest accuracy (94.32 %).

Ma et al. [33] utilized an attention module built into the multi-stage partial network's backbone, and they extracted multi-dimensional information from both the spatial and channel views. To increase the breadth of information about agricultural diseases that can be extracted from photographs of crops, they also added an area pyramid aggregating module that makes use of dilated convolutions to the network.

Guerrero-Ibanez and Reyes-Muñoz [34] included GAN based methods for augmenting data in the process of developing a CNN architecture for disease detection and classification in tomato leaves. The accuracy of disease classification was improved to a level of 99.64%. To begin with, a deep module was presented in the MMDGAN generator to enhance feature extraction of tomato disease leaves. To regulate the overall process of image production, an integrated attention system was then devised, which incorporated a cross attentiveness module with a merged module. Finally, the Markov discriminator was implemented to improve local texture similarity assessment. Saeed et al. [35] considered the diagnosis of tomato leaf diseases by classifying photos of healthy and unhealthy tomato leaves using a classification system. They developed these models by utilizing a publicly available dataset known as PlantVillage, and they achieved a validation accuracy of 99.22%, which was the best possible score.

Ahmad et al. [36] evaluated the efficacy of five conventional deep learning models with regard to the identification of plant diseases across a wide range of environmental variables. The training for these models was done with photos of corn diseases taken from publicly available sources. According to what they found, employing DenseNet169 resulted in maximum validation accuracy (81.60%) in the field of plant disease diagnosis, representing the peak of generalization performance. The classification of tomato leaf disease was the topic of discussion in [37], where a strategy for fine-tuning the created CNN models was presented. An optimization of the hyper parameters was carried out by the authors utilizing the particle swarm optimization technique (PSO). Grid search optimization is used to get the best results for optimizing the weights of these structures. They also suggested a triple and quintuple ensemble model and an approach that classified the datasets called cross-validation. They achieved the best possible classification accuracy of 99.60% by utilizing the ensemble approach.

Francis et al. [38] outlined the automatic generation of features and the creation of prediction systems in agriculture as an application of typical deep learning models. They placed a strong emphasis on the significance of fine-tuning the model, transfer learning, and the segmentation of sick areas. They began by training on a dataset consisting of apple leaves, both healthy and ill. Then, they tested the efficacy of different MobileNet models whose depth multipliers and resolution multipliers varied. Using both Mobilenet and the K means clustering method, they were able to get the greatest accuracy possible, which was 99.7%.

5. Leaf Disease Identification Using Generative Adversarial Network (GAN)

The field of producing synthetic images has seen the introduction of generative adversarial networks, sometimes known as GANs, during the previous half decade. In addition, CNNs have found widespread application in the fields of disease recognition in leaves and pest recognition. CNNs have been utilized in these areas, and their efficacy as a strategy has been demonstrated. Despite this, the most significant challenge, which is that of a restricted training dataset, has been neglected. Because of this, there is now a problem with the data being over fit. In addition, thanks to the development of algorithms that are based on GANs, the accuracy of predictions has improved, and the issue of excessive data fitting due to a lack of available training data has been overcome. GANs are utilized in [24] Good fellow et al. primarily for the purpose of combating the issue of insufficient data. GANs have a structure that is made up of 2 networks, namely a discriminator network and a generator network. Here, the generator is responsible for capturing the training data distribution, whilst a discriminator is responsible for calculating the likelihood of whether an image came from the program that generated it or the data set employed to train. Furthermore, the objective is to improve the generator's capability to tweak the discriminator, which has been provided the training to identify natural images from the ones that have been artificially formed. To use this tactic, dedicated GANs are required that can produce synthetic images. These mock images are used for training a system that can classify leaf diseases and pests accurately. Table 5 shows the comparison analysis of GA based models for crop leaf disease classification.

Table 5. Crop leaf disease classification

Ref	Contribution	Dataset	Performance
[25]	Multimodal GAN images are considered and introduced two stage CNN	Custom dataset with 42 leaf diseases from 16 different plant species	mAP of PDNET-1 = 0.9165 mAP of PDNet-2 = 93.67
[26]	Tranvolution detection network with GAN	PlantDoc,	Precision =51.7%, Recall =48.1% mAP=50.3%
[27]	Three stage pipelined DL architecture by using Faster R-CNN, DCGAN, and ResNet.	GrapeLeaf	NA
[33]	Attention mechanism and spatial pyramid pooling based DL architecture, which uses dilated convolutions	Custom dataset	Accuracy =90.15
[34]	CNN with GAN augmentation	Tomato leaves	Accuracy =99.64%
[35]	Pre-trained CNNs	Plant Village	Accuracy =99.22%
[36]	Comparative analysis of different DL models where DenseNet169 obtained the highest accuracy		Accuracy =81.69
[37]	Optimized deep learning using a meta-heuristic approach	Tomato leaf disease	Accuracy =99.60
[38]	Combined use of transfer learning and fine-tuning. Therefore, MobileNet with KMeans clustering is used.	Tomato leaves	accuracy = 99.7%

Arsenovic et al. [25], in their work, mentioned artificial means to generate crop photos by employing Generative Adversarial Networks (GANs). In addition, throughout the past few years, a number of different variations of GAN architectures have been presented, including CGAN, DCGAN, ProGAN, and StyleGAN. In order to more accurately reflect multimodal data production, the conditional GAN, also known as CGAN, is utilized. According to the findings, the optimal resolution for the leaf images that StyleGAN created was 256 pixels by 256 pixels. Because of the noisy background, these GAN networks did not train well on field photos, which is a problem that has not been rectified despite additional training on field images. Networks trained on GAN-generated images performed around 1% better than networks trained just on natural images on the test set. As a bonus, Plant DiseaseNet (PDNet), a two-stage convolutional neural network, was unveiled as well [25]. The initial stage (PDNet-1) of this process, which predicted the leaf bounding box, also made use of the detector YOLOv3 and the feature extractor Alexnet. In addition, stage two of the plant DiseaseNet, or PDNet-2, is comprised of a softmax layer, a 32-layer CNN architecture, a pooling layer for global averaging, and a fully connected 42-way layer. In terms of map scores, PDNET-1 achieves 0.9165, while PDNET-2 achieves 93.66% accuracy in identifying agricultural diseases. It is worth noting that GANs have huge untapped potential for creating training images automatically and are very beneficial in solving informational difficulties shortage.

As per Zhang et al. [26], conventional deep learning-based techniques have several drawbacks, including (1) the need for expensive hardware and a massive amount of data for training the models. (2) The slow inference speed of models makes them difficult to adapt to real-world manufacturing. The third problem is that models do not generalize well enough. In light of these challenges, this research proposes using a Tranvolution detection network equipped with GAN modules to identify crop diseases. GAN models were first integrated into the attention extraction module, and then GAN modules were built from scratch. After the CNN was integrated with the updated Transformer, they proposed the Tranvolution architecture.

Chen et al. [27] proposed a three-stage DL based pipeline to address the issues, which consisted of a convolutional neural network (Faster R-CNN) for lesion recognition. The lesions on grape leaves were marked using Faster R-CNN so that a lesions dataset could be obtained, which ResNet was utilized to identify. Leaf GAN makes better use of features to produce grape leaf disease images with noticeable disease lesions using a decreasing-channel producer model. The original grape disease photos are then used in conjunction with a discriminator model that makes use of a dense connection technique and instance normalization to produce highly accurate feature extraction results. The training process is then stabilized by using the deep regret diminished function.

6. Leaf Disease Recognition Based on Different Types of Data

As the IoT spreads throughout the agricultural sector, driven by advances in digital technology and recognizing sensors, new sensor technologies emerge and evolve in the directions of being attached, smart, combined, and simplified.

6.1. Ground Image Dataset

Imaging crops from the ground up, such as with a smartphone or digital camera, is known as "crop ground imaging." Many researchers attempted to take pictures of plant leaves in the field, which presented a number of challenges due to the presence of things like complicated backgrounds, shadows, and varying levels of light.

For this goal, conventional machine learning methods were employed by them. SVM models are often used in this research for crop disease diagnoses due to their excellent prediction accuracy. Hyperspectral imaging at close range for early detection of severe drought in barley was achieved using support vector machines [39]. Data from labels and two vegetation indices were used to train the model.

Similar methods for reducing misclassification in disease detection on plant leaves, such as the physical extraction of lesions and the combining of various SVM classifiers (color, texture, and shape attributes) [40]. Using a PCA model, researchers were able to differentiate between plants in good condition and the advancement of golden potato disease [48] based on statistical analysis of some variables.

Hyperspectral pictures of diseased potatoes at various phases of disease development were obtained. The investigation confirmed that spectral data can be used to differentiate between plants in good condition and those that are afflicted with illness. Similarly, the authors in [41] employed hyperspectral images to classify the degree of grey mould infestations on tomato leaves using the decision tree-based classifier C5.0 and KNN. Using ANN with one hidden layer. The authors of [42] estimated the severity of three wheat illnesses. The network achieved an 81% classification accuracy. Table 6 presents the outcome of plant disease detection for ground images.

Table 6. Outcome of plant disease detection for ground images

Data type	ML/DL	Method	Crop	Dataset (no. of images/type)	Accuracy	Reference
Ground images	ML	SVM	Barley	204	68%	[39]
		SVM	Tomato	284	93.90%	[43]
		SVM	Rice	120	73.32%	[47]
		PCA	Potato	120	-	[48]
		KNN	Tomato	212	92.85%	[41]
		ANN	Wheat	630 / multispectral	81%	[42]
	DL	ELM	Tomato	310 / hyperspectral	100	[49]
		ELM	Tobacco	180 / hyperspectral	98%	[50]
		ResNet	Multiple	55,038	99.67%	[50]
		2D- CNN BidGRU	Wheat	90	84.6%	[52]
		ResNet MC1	Multiple	121,955	98%	[53]
		Adapted MobileNet	Tomato	7176	89.2	[54]
		SSCNN	citrus	2939	99%	[55]
		MobileNet	Apple	334	73.50%	[56]
		DenseNet	Tomato	666	95.65%	[57]
		EfficientNet	Multiple	55,038	99.97%	[58]

6.2. UAV Based Imaging

Unmanned Aerial Vehicles (UAVs) are also harnessed as a Precise Agricultural (PA) tool. This tool aids in the supervision and management of crop growth, potential disease progression, and the identification of weeds. This is achievable due to the UAVs' capability to gather images of superior resolution at reduced expenses. Within the realm of agriculture, it plays a significant role by substantially decreasing costs associated with the requirement of an on-site specialist to conduct multiple rounds of comprehensive crop monitoring. UAVs outfitted with integrated cameras and sensors execute adept data collection across expansive fields, facilitating the visualization and comprehensive analysis of field-scale dynamics. Supplementary components further augment the efficacy of crop surveillance methodologies, encompassing the meticulous selection of suitable sensors and intelligent recognition models. Conventional machine learning algorithms are employed for the identification of plant diseases utilizing imagery captured by UAVs. One of the initial models for predicting the extent of plant infections through imagery involved the utilization of the Backpropagation Neural Network (BPNN) model [59].

In this context, the researchers retrieved spectrum information from hyper spectral photos of tomato plants taken with remote sensing. Next, these images were evaluated to examine the severity of light blight disease, which is categorized into 5 stages. The BPNN model was subsequently applied to the mined dataset. The outcomes from the model highlight the possibility of using an Artificial Neural Network (ANN) with backpropagation for spectral-based disease detection prediction. Likewise, researchers in [64] worked on identifying leafroll disease through the usage of Regression Tree methods. This method is based on the spectral and spatial properties of hyper spectral UAV photos of grapevines. Similar to this, investigators in [62] used UAV multispectral images to mine spectral bands, vegetation indices, and biophysical characteristics from both distressed and healthy plants.

They then used ROC analysis to evaluate how well the selected factors identified the existence of the condition. Researchers used a segmentation strategy based on Simple Linear Iterative Clustering in a different study [62] to detect foliar illnesses in soybean plants. Their technique creates super pixels by using the k-means technique. After segmentation, the pictures were classified using a Support Vector Machine (SVM), which achieved a 98.34% accuracy rate. In a different experiment [63], researchers focused on using UAV multispectral photos to identify wheat yellow rust illness. They used a system based on the random forest classifier, which has an accuracy rate of 89.3% and can efficiently differentiate the illness across different developmental periods. Citrus canker was identified using UAV photos in [68] at different phases of the disease's development. The scientists used an artificial neural network called the Radial Basis Function (RBF), which is used in supervised machine learning, for classification. This categorization method achieved a remarkable 92% detection accuracy for the illness. In order to get more precise information on plant features, researchers in [65] derived Vegetation Indices (VIs) from multispectral photographs. The study's conclusions showed that, when utilizing the Ada Boost method, compressing the VIs feature using PCA and merging it with the original data values produced 100% flawless correctness. For classification tasks, including hyperspectral data collected from both healthy and ill avocado trees, Multilayer Perceptions (MLPs) were utilized [67]. In a similar vein, using hyper spectral and thermal pictures obtained with UAVs, the SVM classifier was utilized to identify a fungus that was damaging olive plants [66]. The model's ideal spectral band selection allowed it to reach an accuracy level of 80%. To sum up, traditional machine learning techniques show poor performance that can change depending on the acquisition device and different growth stages.

This limited performance can also be attributed to the feature engineering course, which could lead to significant information loss. To address these limitations, DL models have emerged for crop disease detection, where the image data is collected through UAV. In [20], a sliding window technique was employed on plot images by using CNN based architecture for classification. The outcomes yielded a mean absolute error of 11.72% and a relatively consistent outcome. In [70], differentiation between healthy and diseased maize leaves was accomplished using the ResNet model, achieving the test accuracy of 97.85%. Similarly, in pursuit of detecting disease symptoms in grape leaves [69], the authors adopted a CNN approach, combining pertinent image features with distinct color spaces. The images were transformed into various colorimetric spaces to segregate intensity data from chrominance. The CNN model Net-5 underwent testing with multiple input data combinations and three patch sizes, resulting in the highest accuracy of 95.86%. Table 7 displays the results of the UAV image-based plant disease detection.

7. Using Deep Learning to Combat Crop Disease

The selection of the use of Machine Learning (ML) along with Deep Learning (DL) techniques for Crop Disease Identification is contingent upon several criteria, including the intricacy of the issue, the data at hand, computing capacity, and the intended degree of precision. The following describes the various approaches and their applicability in this field:

7.1. Machine Learning Methods

7.1.1. SVM

SVMs can be effective for binary classification tasks, but they might struggle with more complex multi-class classification problems commonly found in crop disease identification.

Table 7. Outcome of plant disease detection for UAV images

Data type	ML/DL	Method	Crop	Image type	Accuracy	Reference
UAV images	ML	BPNN	Tomato	Hyperspectral	-	[59]
		CART	Vine grape	Hyperspectral	94.1	[60]
		ROC analysis	Vine grape	Multi-spectral	-	[61]
		SLIC + SVM	Soybean	RGB	98.34	[62]
		Random forest	Wheat	Multi-spectral	89.34	[63]
		RBF	Citrus	Multi-spectral	96	[64]
		AdaBoost	Citrus	Multi-spectral	100	[65]
		SVM	Olive	Thermal and hyper-spectral	80	[66]
		MLP	Avocado	Hyperspectral	94	[67]
	DL	ResNet	Maize	RGB	97.85	[68]
		CNN	Potato	Multi-spectral	-	[20]
		Net-5	Grape vine	Multi-spectral	95.86	[69]
		CNN	Maize	RGB	95.1	[70]
		DCNN	Wheat	Hyperspectral	85	[71]
		DCGAN+ inception	Pinus Tree	RGB	-	[73]
		SegNet	grapevine	Multi-spectral	-	[69]
		VddNet	grapevine	Multi-spectral	93.72	[73]

7.1.2. Random Forests (RF) and Decision Trees

These methods work well when dealing with a mix of categorical and numerical data and can handle non-linear relationships. They might be suitable for simpler classification tasks within crop disease identification.

7.1.3. Naive Bayes

Simple and efficient, Naive Bayes methods assume independence between features, which might not be true for all crop disease identification scenarios. They might work well for certain simpler cases.

7.2. Deep Learning Methods

7.2.1. CNN

CNNs are especially well-suited for agricultural disease diagnosis using photos of leaves or crops since they are very good at analysing visual data and are very effective for image-based jobs. From the photos, they can automatically extract pertinent elements.

7.2.2. Recurrent Neural Networks (RNNs)

Suitable for sequential data. In crop disease identification, if there is temporal information involved (like the progression of a disease over time), RNNs might be useful.

7.2.3. Transfer Learning

Utilizing pre-trained models (e.g., using ImageNet-trained models) and optimising them for crop disease identification can be beneficial, especially when labeled data is limited. This approach often works well with CNNs.

7.3. Suitability of ML Models in Crop Disease Identification

7.3.1. Complexity of the Problem

Deep learning methods like CNNs can handle complex patterns and changes in picture data. This makes them useful for determining subtle visual cues associated with different diseases on crops.

7.3.2. Data Availability

DL schemes typically require a huge amount of labeled data to perform well. If labeled datasets are available, CNNs can leverage this data effectively.

7.3.3. Interpretability

Some ML models, like decision trees offer better interpretability compared to deep learning models like CNNs. In scenarios where understanding the reasoning behind predictions is crucial, these models might be preferred.

7.3.4. Computational Resources

Deep learning models, especially large CNN architectures, demand significant computational resources (high-end GPUs) for training. ML models like decision trees or SVMs are less resource-intensive.

Ultimately, a combination of approaches might yield the best results. For instance, using a CNN for image feature extraction and then integrating it with an interpretable ML model for final classification could be a hybrid strategy for accurate disease identification in crops while maintaining some level of interpretability.

8. Plant Disease Dataset

One such open dataset, PlantVillage, has accumulated 54309 photos of plant illnesses on its leaves; this dataset covers 14 different types of fruit and vegetable crops, including apples, blueberries, cherries, grapes, oranges, potatoes, peppers, pumpkins, strawberries, and tomatoes. Corn has 12 photographs of healthy crop leaves in addition to 26 images of diseased ones, seventeen fungal, four bacterial, two mycotic, two viral, and one mite illness.

'Plant Pathology Challenge' for CVPR 2020-FGVC7, The collection contains 3,651 labelled RGB pictures in total, including 1,200 images of the apple scab, 1,399 images of cedar apple rust, 187 images of leaves with several illnesses, and 865 images of apple leaves in good condition.

9. Performance Measurement Parameters

To evaluate the efficacy of the method being presented, numerous measures, including sensitivity, specificity, accuracy, dice score, positive projected value, and area under the curve, have been taken into consideration. These metrics may be calculated as follows:

Performance Metrics	**Computation formula**
Sensitivity S_n	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
Accuracy	$\frac{TP+TN}{TN+TP+FP+FN}$
AUC	$\approx 0.5(Sn+Sp)$

Here, The polar opposites of one another are represented by the phrases FP (False Positive), true negative (TN), True Positive (TP), and False Negative (FN). The genuine positive rate is known as sensitivity (S_n), the false positive and false negative rates are known as specificity (S_p), accuracy is a measure of real prediction, false positives are the wrong positive predictions, and false negatives are the wrong negative predictions. The final result is the AUC, which is calculated as about half of the total of the sensitivity and specificity.

10. Answers to Research Question

In previous Section 2, we discussed several research questions, and based on those questions, we have performed the literature review and identified solutions to those questions, which are as follows:

*SRQ1: "*What cutting-edge machine learning techniques have been applied recently to address the issue of agricultural disease detection*?"*

The complete review discussed various methods for plant leaf disease detection where ML and DL based computer vision methods had been identified as the promising solution; therefore, it has been widely adopted in this domain.

SRQ2: Which crop diseases cause the most damage and are most common?

Several crop diseases can cause significant damage and are widespread, impacting agricultural productivity and food security globally. Some of the most damaging and common crop diseases include Rice Blast, Wheat Rusts (Stripe, Stem, and Leaf Rust), and Late Blight of Potatoes and tomatoes.

SRQ3: What kinds of data sets are there to choose from?

In this context, two datasets are widely used, which are known as the PlantVillage dataset and the Plant Pathology Challenge dataset.

SRQ4: How do crop disease detection experts often measure success?

The TP, TN, FP and FN are identified in order to gauge the effectiveness of these procedures. Accuracy, precision, recall, and f-measure are then estimated.

SRQ5: What are the most popular machine learning frameworks?

Generally, supervised machine learning methods are widely adopted in classification tasks, but the current advancements have focused on increasing the overall accuracy; therefore, ensemble machine learning methods are also adopted where two or more classifications are combined to obtain an accurate classification.

11. Conclusion

In this paper, we presented a foundational understanding of ML/DL techniques. We gave a thorough evaluation of recent research for the usage of DL methods to the problem of crop leaf disease recognition. Assuming a suitable quantity of training data is used, deep learning methods may accurately detect leaf-borne diseases. Hyper-spectral imaging and small-sample disease detection in plant leaves have been discussed, as have the benefits of collecting huge databases with high variation, improving data quality, learning from experience, and visualizing CNN activation maps to enhance classification accuracy. There are, however, a few shortcomings. According to the literature, the majority of DL frameworks operate well with their datasets but not so well on other datasets. This indicates that the model is not very robust. Improved DL models are needed to accommodate the abundance of datasets about diseases.

Several studies have used the data collected by PlantVillage to assess the effectiveness of DL-based frameworks. Despite the large number of photos depicting various plant diseases, this collection is still useful. A comprehensive database of plant diseases in natural settings is thus anticipated. Even seasoned professionals have trouble pinpointing the precise location of invisible disease symptoms and defining pure invisible illness pixels, making it challenging to generate the annotated information necessary for early plant disease detection.

References

[1] Shima Ramesh et al., "Plant Disease Detection Using Machine Learning," *2018 International Conference on Design Innovations for 3Cs Compute Communicate Control*, Bangalore, India, pp. 41-45, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[2] Sunil S. Harakannanavar et al., "Plant Leaf Disease Detection Using Computer Vision and Machine Learning Algorithms," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 305-310, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Anuradha Chug et al., "A Novel Framework for Image-Based Plant Disease Detection using Hybrid Deep Learning Approach," *Soft Computing*, vol. 27, pp. 13613-13638, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Muhammad Hammad Saleem, Johan Potgieter, and Khalid Mahmood Arif, "A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand," *IEEE Access*, vol. 10, pp. 89798-89822, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] M. Nandhini et al., "Deep Learning Model of Sequential Image Classifier for Crop Disease Detection in Plantain Tree Cultivation," *Computers and Electronics in Agriculture*, vol. 197, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] R. Arumuga Arun, and S. Umamaheswari, "Effective Multi-Crop Disease Detection Using Pruned Complete Concatenated Deep Learning Model," *Expert Systems with Applications*, vol. 213, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Junde Chen et al., "Stacking Ensemble Model of Deep Learning for Plant Disease Recognition," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 12359-12372, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] S.K. Mahmudul Hassan, and Arnab Kumar Maji, "Plant Disease Identification Using a Novel Convolutional Neural Network," *IEEE Access*, vol. 10, pp. 5390-5401, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Poornima Singh Thakur, Tanuja Sheorey, and Aparajita Ojha, "VGG-ICNN: A Lightweight CNN Model for Crop Disease Identification," *Multimedia Tools and Applications*, vol. 82, pp. 497-520, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Yousef Methkal Abd Algani et al., "Leaf Disease Identification and Classification Using Optimized Deep Learning," *Measurement: Sensors*, vol. 25, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] J. Arun Pandian et al., "Plant Disease Detection Using Deep Convolutional Neural Network," *Applied Sciences*, vol. 12, no. 14, pp. 1-14, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] Rabbia Mahum et al., "A Novel Framework for Potato Leaf Disease Detection Using an Efficient Deep Learning Model," *Human and Ecological Risk Assessment: An International Journal*, vol. 29, no. 2, pp. 303-326, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Zhaoyi Chen et al., "Plant Disease Recognition Model Based on Improved YOLOv5," *Agronomy*, vol. 12, no. 2, pp. 1-14, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Yusuke Kawasaki et al., "Basic Study of Automated Diagnosis of Viral Plant Diseases Using Convolutional Neural Networks," *Advances in Visual Computing, Lecture Notes in Computer Science*, vol. 9475, pp. 638-645, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[15] Halil Durmuş, Ece Olcay Güneş, and Mürvet Kırcı, "Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning," *2017 6th International Conference on Agro-Geoinformatics*, Fairfax, VA, USA, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Peng Jiang et al., "Real-Time Detection of Apple Leaf Diseases using Deep Learning Approach Based on Improved Convolutional Neural Networks, *IEEE Access*, vol. 7, pp. 59069-59080, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jayme Garcia Arnal Barbedo, "Plant Disease Identification from Individual Lesions and Spots Using Deep Learning," *Biosystems Engineering*, vol. 180, pp. 96-107, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sharifah Farhana Syed-Ab-Rahman, Mohammad Hesam Hesamian, and Mukesh Prasad, "Citrus Disease Detection and Classification Using End-to-End Anchor-Based Deep Learning Model," *Applied Intelligence*, vol. 52, pp. 927-938, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Wu Dake, and Ma Chengweim, "The Support Vector Machine (SVM) Based Near-Infrared Spectrum Recognition of Leaves Infected by the Leafminers," *First International Conference on Innovative Computing, Information and Control (ICICIC'06)*, Beijing, China, vol. 1, pp. 448-451, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[20] Julio M. Duarte-Carvajalino et al., "Evaluating Late Blight Severity in Potato Crops using Unmanned Aerial Vehicles and Machine Learning Algorithms," *Remote Sensing*, vol. 10, no. 10, pp. 1-17, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[21] Shan-e-Ahmed Raza et al., "Automatic Detection of Diseased Tomato Plants Using Thermal and Stereo Visible Light Images," *PLoS One*, vol. 10, no. 4, pp. 1-20, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[22] Usama Mokhtar et al., "Identifying Two of Tomatoes Leaf Viruses Using Support Vector Machine," *Information Systems Design and Intelligent Applications: Proceedings of Second International Conference INDIA 2015*, pp. 771-782, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[23] Mohammed Brahimi, Kamel Boukhalfa, and Abdelouahab Moussaoui, "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization," *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299-315, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ian Goodfellow et al., "Generative Adversarial Nets," *Advances in Neural Information Processing Systems*, vol. 27, 2014. [Google Scholar] [Publisher Link]

[25] Marko Arsenovic et al., “Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection,” *Symmetry*, vol. 11, no. 7, pp. 1-21, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[26] Yan Zhang et al., “Automatic Plant Disease Detection based on Tranvolution Detection Network with GAN Modules using Leaf Images,” *Frontiers in Plant Science*, vol. 13, pp. 1-20, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[27] Yiping Chen, and Qiufeng Wu, “Grape Leaf Disease Identification with Sparse Data via Generative Adversarial Networks and Convolutional Neural Networks,” *Precision Agriculture*, vol. 24, pp. 235-253, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[28] Mamta Gehlot, and Geeta Chhabra Gandhi, “EffiNet-TS”: A Deep Interpretable Architecture Using EfficientNet for Plant Disease Detection and Visualization,” *Journal of Plant Diseases and Protection*, vol. 130, pp. 413-430, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[29] Muhammad Attique Khan et al., “Cucumber Leaf Diseases Recognition Using Multi Level Deep Entropy-ELM Feature Selection,” *Applied Sciences*, vol. 12, no. 2, pp. 1-19, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[30] L.G. Divyanth, Aanis Ahmad, and Dharmendra Saraswa, “A Two-Stage Deep-Learning Based Segmentation Model for Crop Disease Quantification based on Corn Field Imagery,” *Smart Agricultural Technology*, vol. 3, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[31] Rabindra Nath Nandi et al., “Device-Friendly Guava Fruit and Leaf Disease Detection Using Deep Learning,” *Machine Intelligence and Emerging Technologies*, pp. 49-59, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[32] Lai Zhi Yong et al., “Automatic Disease Detection of Basal Stem Rot Using Deep Learning and Hyperspectral Imaging,” *Agriculture*, vol. 13, no. 1, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[33] Wei Ma et al., “Crop Disease Detection Against Complex Background Based on Improved Atrous Spatial Pyramid Pooling,” *Electronics*, vol. 12, no. 1, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[34] Antonio Guerrero-Ibañez, and Angelica Reyes-Muñoz, “Monitoring Tomato Leaf Disease through Convolutional Neural Networks,” *Electronics*, vol. 12, no. 1, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[35] Alaa Saeed et al., “Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks,” *Agriculture*, vol. 13, no. 1, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[36] Aanis Ahmad, Aly El Gamal, and Dharmendra Saraswat, “Toward Generalization of Deep Learning-Based Plant Disease Identification under Controlled and Field Conditions,” *IEEE Access*, vol. 11, pp. 9042-9057, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[37] Hasan Ulutaş, and Veysel Aslantaş, “Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model,” *Electronics*, vol. 12, no. 4, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[38] Mercelin Francis et al., “Smart Farm-Care Using a Deep Learning Model on Mobile Phones,” *Emerging Science Journal*, vol. 7, no. 2, pp. 480-497, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[39] Jan Behmann, Jörg Steinrücken, and Lutz Plümer, “Detection of Early Plant Stress Responses in Hyperspectral Images,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 93, pp. 98-111, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[40] Youssef Es-Saady et al., “Automatic Recognition of Plant Leaves Diseases Based on Serial Combination of Two SVM Classifiers,” *2016 International Conference on Electrical and Information Technologies*, Tangiers, Morocco, pp. 561-566, 2016. [CrossRef] [Google Scholar] [Publisher Link]
[41] Chuanqi Xie, Ce Yang, and Yong He, “Hyperspectral Imaging for Classification of Healthy and Gray Mold Diseased Tomato Leaves with Different Infection Severities,” *Computers and Electronics in Agriculture*, vol. 135, pp. 154-162, 2017. [CrossRef] [Google Scholar] [Publisher Link]
[42] Romain Bebronne et al., “In-Field Proximal Sensing of Septoria Tritici Blotch, Stripe Rust and Brown Rust in Winter Wheat by Means of Reflectance and Textural Features from Multispectral Imagery,” *Biosystems Engineering*, vol. 197, pp. 257-269, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[43] Ismail El Massi et al., “Hybrid Combination of Multiple SVM Classifiers for Automatic Recognition of the Damages and Symptoms on Plant Leaves,” *Image and Signal Processing, Lecture Notes in Computer Science*, vol. 9680, pp. 40-50, 2016. [CrossRef] [Google Scholar] [Publisher Link]
[44] Shan Suthaharan, *Support Vector Machine*, Machine Learning Models and Algorithms for Big Data Classification, pp. 207-235, 2016. [CrossRef] [Google Scholar] [Publisher Link]
[45] Y.H. Gu et al., “BLITE-SVR: New Forecasting Model for Late Blight on Potato Using Support-Vector Regression,” *Computers and Electronics in Agriculture*, vol. 130, pp. 169-176, 2016. [CrossRef] [Google Scholar] [Publisher Link]
[46] Anshul Bhatia, Anuradha Chug, and Amit Prakash Singh, “Hybrid SVM-LR Classifier for Powdery Mildew Disease Prediction in Tomato Plant,” *2020 7th International Conference on Signal Processing and Integrated Networks*, Noida, India, pp. 218-223, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[47] Harshadkumar B. Prajapati, Jitesh Shah, and Vipul K. Dabhi, “Detection and Classification of Rice Plant Diseases,” *Intelligent Decision Technologies*, vol. 11, no. 3, pp. 357-373, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[48] Daniel Atherton, Ruplal Choudhary, and Dennis Watson, "Hyperspectral Remote Sensing for Advanced Detection of Early Blight (Alternaria solani) Disease in Potato (Solanum tuberosum) Plants Prior to Visual Disease Symptoms," *Proceedings of the 2017 ASABE Annual International Meeting*, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[49] Chuanqi Xie et al., "Detection of Early Blight and Late Blight Diseases on Tomato Leaves Using Hyperspectral Imaging," *Scientific Reports*, vol. 5, pp. 1-11, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[50] Hongyan Zhu et al., "Hyperspectral Imaging for Presymptomatic Detection of Tobacco Disease with Successive Projections Algorithm and Machine-Learning Classifiers," *Scientific Reports*, vol. 7, pp. 1-12, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[51] Mohammed Brahimi et al., *Deep Learning for Plant Diseases: Detection and Saliency Map Visualisation*, Human and Machine Learning, Springer, Cham, pp. 93-117, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[52] Xiu Jin et al., "Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field," *Remote Sensing*, vol. 10, no. 3, pp. 1-20, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[53] Artzai Picon et al., "Crop Conditional Convolutional Neural Networks for Massive Multi-Crop Plant Disease Classification Over Cell Phone Acquired Images Taken on Real Field Conditions," *Computers and Electronics in Agriculture*, vol. 167, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[54] Azeddine Elhassouny, and Florentin Smarandache, "Smart Mobile Application to Recognize Tomato Leaf Diseases Using Convolutional Neural Networks," *2019 International Conference of Computer Science and Renewable Energies*, Agadir, Morocco, pp. 1-4, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[55] Utpal Barman et al., "Comparison of Convolution Neural Networks for Smartphone Image Based Real Time Classification of Citrus Leaf Disease," *Computers and Electronics in Agriculture*, vol. 177, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[56] Chongke Bi et al., "MobileNet Based Apple Leaf Diseases Identification," *Mobile Networks and Applications*, vol. 27, pp. 172-180, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[57] Maryam Ouhami et al., "Deep Transfer Learning Models for Tomato Disease Detection," *Image Signal Processing, 9th International Conference*, Marrakesh, Morocco, pp. 65-73, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[58] Ümit Atila et al., "Plant Leaf Disease Classification using EfficientNet Deep Learning Model," *Ecological Informatics*, vol. 61, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[59] X. Wang et al., "Spectral Prediction of Phytophthora Infestans Infection on Tomatoes Using Artificial Neural Network (ANN), *International Journal of Remote Sensing*, vol. 29, no. 6, pp. 1693-1706, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[60] Sarah L. MacDonald et al., "Remote Hyperspectral Imaging of Grapevine Leafroll-Associated Virus 3 in Cabernet Sauvignon Vineyards," *Computers and Electronics in Agriculture*, vol. 130, pp. 109-117, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[61] Johanna Albetis et al., "Detection of Flavescence Dorée Grapevine Disease Using Unmanned Aerial Vehicle (UAV) Multispectral Imagery," *Remote Sensing*, vol. 9, no. 4, pp. 1-20, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[62] Everton Castelão Tetila et al., "Identification of Soybean Foliar Diseases Using Unmanned Aerial Vehicle Images," *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 12, pp. 2190-2194, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[63] Jinya Su et al., "Wheat Yellow Rust Monitoring by Learning from Multispectral UAV Aerial Imagery," *Computers and Electronics in Agriculture*, vol. 155, pp. 157-166, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[64] Jaafar Abdulridha, Ozgur Batuman, and Yiannis Ampatzidis, "UAV-Based Remote Sensing Technique to Detect Citrus Canker Disease Utilizing Hyperspectral Imaging and Machine Learning," *Remote Sensing*, vol. 11, no. 11, pp. 1-22, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[65] Yubin Lan et al., "Comparison of Machine Learning Methods for Citrus Greening Detection on UAV Multispectral Images," *Computers and Electronics in Agriculture*, vol. 171, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[66] T. Poblete et al., "Detection of Xylella Fastidiosa Infection Symptoms with Airborne Multispectral and Thermal Imagery: Assessing Bandset Reduction Performance from Hyperspectral Analysis," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 162, pp. 27-40, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[67] Jaafar Abdulridha et al., "Detecting Powdery Mildew Disease in Squash at Different Stages Using UAV-Based Hyperspectral Imaging and Artificial Intelligence," *Biosystems Engineering*, vol. 197, pp. 135-148, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[68] Tyr Wiesner-Hanks et al., "Image Set for Deep Learning: Field Images of Maize Annotated with Disease Symptoms," *BMC Research Notes*, vol. 11, pp. 1-3, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[69] Mohamed Kerkech, Adel Hafiane, and Raphael Canals, "Deep Leaning Approach with Colorimetric Spaces and Vegetation Indices for Vine Diseases Detection in UAV Images," *Computers and Electronics in Agriculture*, vol. 155, pp. 237-243, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[70] Harvey Wu et al., "Autonomous Detection of Plant Disease Symptoms Directly from Aerial Imagery," *The Plant Phenome Journal*, vol. 2, no. 1, pp. 1-9, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[71] Xin Zhang et al., "A Deep Learning-Based Approach for Automated Yellow Rust Disease Detection from High-Resolution Hyper-Spectral UAV Images," *Remote Sensing*, vol. 11, no. 13, pp. 1-16, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[72] Gensheng Hu et al., "Recognition of Diseased Pinus Trees in UAV Images Using Deep Learning and Adaboost Classifier," *Biosystems Engineering*, vol. 194, pp. 138-151, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[73] Mohamed Kerkech, Adel Hafiane, and Raphael Canals, "VddNet: Vine Disease Detection Network Based on Multispectral Images and Depth Map," *Remote Sensing*, vol. 12, no. 20, pp. 1-18, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[74] Yi Fang, and Ramaraja P. Ramasamy, "Current and Prospective Methods for Plant Disease Detection," *Biosensors*, vol. 5, no. 3, pp. 537-561, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[75] Federico Martinelli et al., "Advanced Methods of Plant Disease Detection. A Review," *Agronomy for Sustainable Development*, vol. 35, pp. 1-25, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[76] Sudau Eh Teet, and Norhashila Hashim, "Recent Advances of Application of Optical Imaging Techniques for Disease Detection in Fruits and Vegetables: A Review," *Food Control*, vol. 152, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[77] Stefan Thomas et al., "Benefits of Hyperspectral Imaging for Plant Disease Detection and Plant Protection: A Technical Perspective," *Journal of Plant Diseases and Protection*, vol. 125, pp. 5-20, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[78] Tiago Domingues, Tomás Brandão, and João C. Ferreira, "Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey," *Agriculture*, vol. 12, no. 9, pp. 1-23, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[79] Anshul Bhatia, Anuradha Chug, and Amit Prakash Singh, "Hybrid SVM-LR Classifier for Powdery Mildew Disease Prediction in Tomato Plant," *2020 7th International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, India, pp. 218-223, 2020. [CrossRef] [Google Scholar] [Publisher Link]