Applied Soft Computing 145 (2023) 110534

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Review article

Leaf disease detection using machine learning and deep learning: Review and challenges

Chittabarni Sarkar [a], Deepak Gupta [b,*], Umesh Gupta [c], Barenya Bikash Hazarika [d]

[a] Department of Computer Science & Engineering, National Institute of Technology Arunachal Pradesh, Jote 79113, India
[b] Department of Computer Science & Engineering, Motilal Nehru National Institute of Technology Allahabad, Prayagraj 211004, India
[c] Department of Computer Science & Engineering, Bennett University, Greater Noida, U.P., India
[d] Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India

A R T I C L E I N F O

Article history:
Received 5 January 2023
Received in revised form 7 June 2023
Accepted 13 June 2023
Available online 22 June 2023

Keywords:
Plant disease
Machine learning
Deep learning
Recognition models
Leaf species

A B S T R A C T

Identification of leaf disorder plays an important role in the economic prosperity of any country. Many parts of a plant can be infected by a virus, fungal, bacteria, and other infectious organisms but here we mainly considered the detection of leaf disease of a plant as a research topic. We have performed an in-depth study of this topic from 2010 to 2022 and found that many researchers use multispectral or hyperspectral imaging to study crop diseases. Machine learning (ML) and deep learning (DL) models are used to classify different types of leaf diseases. We made a workflow mechanism to help researchers in this field. Support vector machine (SVM), Random Forest, and multiple twin SVM (MTSVM) are popular ML models for predicting leaf disease, while convolutional neural networks (CNN), visual geometry group (VGG), ResNet (RNet), GoogLeNet, deep CNN (DCNN), back propagation neural networks (BPNN), DenseNet (DNet), LeafNet (LN), and LeNet are common deep learning models used for detecting leaf disease. Among these deep learning models, it is evident that models like CNN, VGG, and ResNet are highly capable at finding diseases in leaves. The performance of the algorithms is generally evaluated using F1 score, precision, accuracy and others. This review will be helpful for the researchers who are working in this area and looking for various efficient ML and DL-based classifiers for leaf disease detection.

Contents

* Corresponding author.
E-mail addresses: chittabarni.1@gmail.com (C. Sarkar), deepakg@mnnit.ac.in (D. Gupta), er.umeshgupta@gmail.com (U. Gupta), barenya1431@gmail.com (B.B. Hazarika).

https://doi.org/10.1016/j.asoc.2023.110534
1568-4946/

1. Introduction

This section gives an overview of this research study with several subheadings that briefly discuss the challenges and techniques of leaf disease detection, the objective of this research work, a major contribution of this review and the search process. Moreover, the impact of different kinds of noise techniques with their important parameters has been illustrated in a tabular manner.

1.1. Overview

Leaf disease is a kind of phenomenon to the natural growth of a plant which is not only generated hurdles in agribusiness but is also responsible for hampering the agricultural production of a country. Several types of bacteria, fungi, viruses [1], and other natural infectious organisms are the main causes of leaf disease in their life cycles. There are many ways to detect and classify different kinds of leaf stresses. The first option is direct observation via naked eyes which is not a prominent process. Secondly, one can investigate the leaf stresses either by manual process or applying any machine learning (ML) algorithms. As far as many researchers have concerned that visual observation or any instrument such as microscope-based observation is a very slow process, which cannot take speedy action before spreading the disease in leaves. In this similar trend, the next better option which is considered in many types of research to apply some ML techniques over plant leaves. In the early ages, one cannot easily detect the disease of leaves before spreading them by using prior knowledge. Thus, the identification of leaf diseases is one of the challenging area of researches in image processing (IP), ML, as well as computer vision [2–4].

1.2. Challenges of leaf disease detection

1.2.1. Issues to deal with image processing

1. Various image processing algorithms [5,6] have been used to recognize and categorize leaf diseases, but practically every IP technique faces numerous problems, as listed below:
2. Noise is one kind of barrier in image processing that reduces efficiency and effectiveness badly. This type of interruption is generated by electronic devices and lighting effects. The presence of noise such as Gaussian and pulse noise in a leaf image may create a hindrance to performing the prediction.
3. Defocused images which are usually captured by electronic devices are one of the major barriers in this experiment. This kind of image cannot be observable clearly due to defocused images becoming blurred.
4. Generally, most researchers adopt datasets that are available in many repositories. Few of them capture images of infected leaves from agricultural fields for their experiment purpose but the process of capturing images is another barrier.
5. These researchers also have the challenging task to deal with different weather conditions, the direction of capturing an image, the distance between electronic devices and infected leaves and different occlusion-based images, and many more.
6. One can obtain several images for different configurations by using various electronic devices namely mobile phones, digital cameras, etc. Selecting an appropriate electronic device is also an important task. The major issue of mobile phone images is blurred as it fails to focus objects clearly. Similarly, a digital camera can capture images of infected leaves but direction and distance from capturing objects are other obstacles to the device.
7. Selecting a large image for the research study is another difficult task. Though each and every piece of information of a large image may provide a prominent impact, even Blurring is also one of the hurdles in the analysis of leaf disease detection.
8. Many researchers have used drone cameras for capturing images of infected leaves in various agricultural fields. The basic demits of this camera are affected by weather and short flight time. With those disadvantages, researchers have adopted drone cameras and obtained several classification outcomes based on different models' configurations. This manuscript has not collected images that are captured by a drone camera.

Various techniques of image filtering are generally used such as box filter [7], Gaussian filter [7], Gradient, and Laplacian filter [7] to avoid noise-related problems in IP. Feature extraction techniques such as thresholding, Blob extraction, template matching, Hough transformation, and generalized histogram of oriented gradients (HoG) transformation are helpful in the identification of different types of leaf disease. The extraction of features from a leaf image is a bit difficult when the irregular presence or patterns of the disease occur randomly. By using popular feature extraction methods, various features of the infected leaf image like the background leaf image, the affected part of the leaf, and the green area of the leaf can be effortlessly extracted. Identification of the leaf disease in an image is a critical task because that image contains a variety of shapes, forms, and colors. Traditional methods cannot work properly in the recognition of leaf disease. Sunny and cloudy weather is also another kind of challenge. These challenges create problems in the recognition of multiple types of disease in leaf images. Introducing various kinds of noises in the images can be represented in a tabular format and the representation is as follows:

1.2.2. Issues to cope with climate change

The impact of weather change is one of the major issues in a plant's life cycle. Leaves are also affected due to weather changes. Infection of leaves gradually increased according to the variation of temperatures. Crane-Droesch [8] discussed the impact of climate change in an agricultural field, and ML-based algorithms have been adopted for crop yield prediction. The impact of rapid weather change not only decreases the lifetime of a plant but also causes a problem with the quick diagnosis of infected plants or leaves. Bebber [9] explained in the research study, how the effect of fungus has been increased on banana leaves due to weather changes and the development of black Sigatoka disease. In the research work, it is mentioned that the risk of black Sigatoka disease escalates very rapidly, and its impact also influenced the health of leave due to climate change. Afzal et al. [10] described the effect of temperature, which is an important factor for planting as choosing an appropriate planting time prevents disease and pests. Moreover, Caldeira et al. [11] have shown the effect of climate on cotton leaves, and to recognize lesions of cotton leaves he has used the deep learning-based RestNet50 method. Ahmad and Muhammad [12] discussed the threats to agriculture due to environmental risks and estimated the effect of climate change on wheat yield.

1.2.3. Impacts of pests and pathogens

Irrespective of the weather change several pests and pathogens like viruses, bacteria and fungi also play vital roles in the case of leaf or plant disease. Wakelin et al. [13] illustrated that drought helps plant pathogens by influencing leaf apertures as these are the main gateways of infesting. Savary et al. [14] provided mathematical estimations of losses caused by several pathogens and pests for five different crops namely rice, wheat, maize, potato end soybean. Juroszek et al. [15] explained in the research study, how climate change, as well as pathogens, hamper the plant's life cycle. It is also mentioned that several extreme weather events like storms and heavy rain can bring success for plant pathogens and pests. Rizzo et al. [16] demonstrated the basic relationship between animals and plants that have been often threatened by plant pathogens and pests. Grabka et al. [17] provided a concept of fungal endophytic as a protective idea against non-insect organisms such as fungi, bacteria, nematodes, viruses, and mites.

1.3. Machine learning and deep learning techniques for detection of leaf disease

As it has been observed that agricultural industry of many countries in the world is suffering from food problems due to less production from the plants. So, different diseases of plants diminish the required product in terms of quantity and quality such as fruits, flowers, vegetables, leaves, and wood. Early detection of leaf disease not only reduces the spreading of disease but also helps farmers by identifying types of infections in tainted plants. In recent days, machine learning techniques have become very useful in the diagnosis of leaf disease. This survey has been conducted to list out several ML, DL classification techniques that have been used for leaf detection namely support vector machine (SVM), k nearest neighbor (KNN), artificial neural networks (ANN), convolutional neural network (CNN), and deep CNN (DCNN) and others.

1.3.1. Machine learning techniques for the detection of leaf disease

ML is a classical approach that enables machines to act as human behavior. Various models such as SVM, k-means clustering (KMC), decision tree (DT), and random forest (RF) help to learn machines using the same experience. Several research domains including agriculture adapt the ML technique for their multi-disciplinary activity. Machine learning algorithms have been applied to find out several leaf stresses as well as helpful in the identification of distinct species.

1.3.1.1. ANN Classifier. This computational model is a part of ML and pattern recognition algorithms that are also important in the field of leaf disease identification. In 1958, psychologist, Rosenblatt proposed the concept of ANN [18]. Al Bashish et al. [19] implemented ANN as a classifier to recognize the extracted features of cotton's infected leaves and obtained 93% classification accuracy. Wang et al. [20,21] applied the principal component analysis (PCA) technique to minimize the dimension of the extracted features and introduced the BPNN classification technique for the identification of grapes and wheat disease. In recent studies, variations of ANN namely bacterial foraging optimization based radial basis function neural network (BRBFNN BFO) [22] and back propagation ANN (BP-ANN) [23] have shown successful classification results in terms of precision and validation evaluation partition coefficient (Vpc) and validation evaluation partition entropy (Vpe) performance parameters. Pham et al. [24] applied the ANN model as an early disease classifier for mango leaves.

1.3.1.2. KNN Classifier. This algorithm is also used as a classifier of leaf disease. In 1975, Friedman et al. proposed this K-nearest neighbor algorithm. Similar to SVM, this method can be applied to multiple classes. Liaghat et al. [25] used this model for fatal fungal (Ganoderma) disease of oil palm plantations and obtain 97% classification accuracy. Zhang et al. [26] implemented this algorithm for identifying five distinct diseases of maize leaves and obtained 91% classification accuracy. Fuzzy combined KNN [27] is a variation of the KNN method that also provides significant outcomes in terms of a 98.38% accuracy value [28]. Devi et al. [29] used a KNN classifier for detecting five different classes as Early leaf (EL) spot, Late leaf (LL) spot, Rust, Bud necrosis, and Alternia spot irritation of groundnut leaves. Singh et al. [30] also considered a KNN classifier for comparison analysis to detect applied leaf disease.

1.3.1.3. SVM Classifier. Cortes and Vladimir [31] first proposed the concept of SVM by using the maximum margin theory and gave a solution for binary classification problems. SVM is a widely used ML approach for detecting leaf disease. Hyperspectral imaging, which captures and processes information from the electromagnetic spectrum reflectance, is also highly popular in the study of leaf disease identification, in addition to collected digital photos or preconfigured image data of sick leaves. Here also ML technique specifically SVM [32] provides a successful outcome. Variation of this technique namely multi-birth SVM (MBSVM) by Yang et al. [33] has also provided significant results. Bhange and Hingoliwala [34] applied the SVM model to recognize pomegranate leaf disease and obtained 92% successful accuracy. Neural network ensemble SVM [35–37] is another variation of the SVM technique that has achieved great success in this study. Wani et al. [38] adopted several ML and DL-related models for leaf disease detection and among these models, SVM has achieved 97.5% accuracy using radial basis function (RBF) kernel. Thomas et al. [39] used an SVM classifier for comparison analysis to detect hyperspectral images of potato late blight disease.

1.3.1.4. TSVM Classifier. Inspired by the SVM, Jayadeva and Suresh [40] proposed the concept of twin SVM (TWSVM) using two non-parallel hyperplanes in the field of binary classification i.e., infected area and non-infected area of the leaf. Tomar and Agarwal [41] proposed the least squares twin support vector machine (LSSVM) concept for leaf disease detection and obtained a significant outcome. Laxmi and Gupta [42] proposed a fuzzy twin support vector machine (FTSVM) model to recognize plant leaf images.

1.3.1.5. ELM Classifier. Guang-Bin et al. [43] proposed the concept of an ELM classifier. Bhatia et al. [44] first applied this architecture in the field of leaf disease detection for highly imbalanced datasets. They have observed the classification result of this model by considering AUC and classification accuracy (CA) and it provides maximum values for CA and area under the curve (AUC) i.e., 89.19% and 88.57%. Kumar et al. [45] used this extreme learning machine (ELM) classifier to share out proper class labels of selected plant leaf images [46].

1.3.2. Deep learning techniques for detection of leaf disease

Chawal and Sanjeev [47] applied the TSVM model to identify rice leaf disease and the performance of this model obtained 95% classification accuracy. DL models provide an awe-inspiring opportunity for the research world to enhance the topic of leaf disease classification and recognition. Various DL techniques were already successfully implemented in this crucial area and provided satisfactory performance as compared to other methods [48].

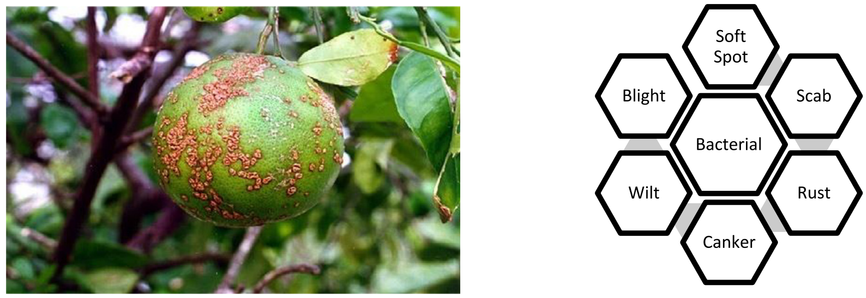
1.3.2.1. CNN Classifier. CNN is one of the important DL-based classifiers for imaging data. Yann LeCun first introduced CNN or ConvNet model in 1980 [49,50]. Kawasaki et al. [51] applied the CNN model for classifying cucumber leaf disease, and it obtains 94.9% classification accuracy. Just like other techniques, CNN has some drawbacks like the requirement of huge parameters and overfitting problems. Hinton et al. [52] have introduced the dropout concept in a fully connected layer which reduces many parameters to avoid the over-fitting problem. Dyrmann et al. [53] considered CNN model for recognizing leaf disease. Similarly, Liu et al. [54] have introduced a global pooling concept to reduce CNN's shortfall and improved the performance of the architecture. Lu et al. [55] this survey work used CNN model to classify apple leaf diseases. Ferentinos [56] applied this model to 25 several plants in a set of 58 distinct classes of plants and diseases and he achieved 99.53% classification accuracy. Annabel et al. [57] has shown the advantage of CNN for leaf disease detection. Agarwal et al. [58] and Trivedi et al. [59] applied the CNN model to the detection of tomato leaf sickness where 91.2% identification accuracy is gained over nine distinct diseases and one healthy class. Huang et al. [60] used a novel deep learning technique for tomato leaf disease detection. Maria et al. [61] proposed CNN-based algorithms as well as ML and DL algorithms where CNN provides significant outcomes. Bhujel et al. [62] applied DL networks for detecting gray mold disease of strawberry leaf images.

1.3.2.2. CNN's Variants. CNN and its variations such as region-based fully convolutional neural network (R-FCN), faster region-based CNN (Faster R-CNN) have been applied in agricultural research work as well as various fields of computations. Ji et al. [63] proposed a 3D CNN model that can easily recognize crops by considering multi-temporal remote sensing images and achieved 93.9%, and 90.20% success rates on the 2015 GF1 dataset using two performance parameters such as OA and kappa. Recent studies focus on hyperspectral images with the consideration of well-known image datasets such as Plant Village's, Internal feeding worm (IFW) database of the Comprehensive automation for speciality crops (CASC-IFW), and Apple Leaf Disease Detection (ALDD) as well as include a very limited imbalanced dataset using different CNN models and synthetic minority over-sampling technique (SMOTE) to observe the performance [64]. Dananjayan et al. [65] have used optical annotated leaf images for obtaining better results for leaf disease detection. Thus, the performance of DL architectures has a meaningful position in the research world in comparison to machine learning methods. Yadav et al. [66] proposed DL based model for detecting disease of peach leaves. Khan et al. [67] applied DL based model to recognize infection of apple leaves. Shah et al. [68] implememted variant CNN model and obtained significant classification outcome for detecting leaf disease.

1.3.2.3. Transfer Learning Models. Transfer learning (TL) is a technique for representing features from a pre-trained model without having to retrain the model. Models such as Inception, VGG, ResNet, and Xception are widely used as transfer learning models. DCNN is another variation of CNN with more layers namely VGG 16, Inception V4, ResNet, DenseNet that provide significant results. Here the only difference is that DCNN considers small datasets and generate unsatisfactory result whereas transfer learning algorithms consider large dataset and solve this problem. Waldamichael et al. [69] applied DCNN based MobileNetV2 for coffee disease detection to observe the performance of this model [70]. Kawasaki et al. [51] introduced CNN based model with a 4-fold cross-validation method that is used to classify 800 cucumber leaf images with two distinct diseases and normal leaves and achieved 94.9% accuracy. Ren et al. [71] proposed region proposal networks to detect infection of leaves. Hu et al. [72] employed the VGG16 model, which included SVM for segmentation and improved conditional deep convolutional adversarial generative networks for data augmentation (C-DCGAN), to detect tea leaf illness with a 90% accuracy-recognition performance. Ganatra and Patel [73,74] implemented fine-tuning DL models such as VGG 16, Inception V4, ResNet (RNet), DenseNet (DNet) with 50, 101 layers to evaluate the recognition of leaf disease. Qi et al. [75] also applied DCNN based architectures such as RNet-50, DNet-121, and logistic regression [18] methods where ResNet50 provides better performance such as 97.59% accuracy after considering data augmentation and stacking ensemble. Algaashani et al. [76] proposed MobileNetV2 and NASNetMobile (NASNet) to obtain the best classification outcome of leaf disease.

1.4. Objectives of the review

The main goal of this research is to draw attention to the research work of leaf disease detection by demonstrating the workflow method used by researchers in diverse literature. This research study went over picture pre-processing techniques, segmentation, feature extraction, and classification approaches, as well as an overview of ML and DL algorithms that have been effectively deployed for leaf disease diagnosis. However, our study has majorly focused on the research between 24th June 2010 to 30th December 2022. A compilation of SCI/SCIE and Scopus indexed publications is also presented to illustrate the high-quality works that were released between June 2010 and December 2022. As a result, this review article will be beneficial for researchers interested in working in the field of leaf disease detection. Finally, it offers comprehensive information on isolated deep learning and machine learning models so that researchers can more effectively apply those models.



(a) **(b)**

Fig. 1. (a): The bacterially infected citrus fruit, (b): Classification of bacterial-based diseases.

1.5. Major contribution of this review

This survey study provides relevant information on various leaf disease detection techniques that have been implemented between June 2010 and December 2022. It also delivers a gist of this research work that can be listed as follows and this listed form will be convenient for researchers before going through the whole research work.

a It gives the benefits and difficulties of ML and DL techniques in the topic of leaf disease detection.
b It also specifically mentions which algorithms have been implemented most here from ML and DL models.
c Represents all datasets adopted by the researchers in a tabular form and provides their information.
d It gives the idea of how many research studies have been selected for universities, government organizations, private organizations, industries, and collaboration between universities and industry.
e Moreover, it illustrates the challenges of image acquisition.
f Further, from this study, an author can understand which algorithm and dataset can be selected as per his or her requirement.

1.6. Strengths and weaknesses of this review

1.6.1. Strength

This research work has provided information on image preprocessing, dataset, disease, feature extraction, and classification in tabular form from 2010 to 2022. That will be very easier for the researchers to have an overview of the recent work in this area. In addition to that, a lot of information from the previous works is represented using graphical interfaces. That will be also helpful for the researchers.

1.6.2. Weakness

There is no doubt that in this review the AI models that have been used earlier for plant leaf disease detection are not fully summarized. But they might not be enough for future unknown environmental challenges. Because of the diversity of natural conditions, it is difficult for AI technology to establish a standard for detecting leaf diseases. In addition to that it is a challenging task to pick up a proper AI model for leaf disease detection. In this review article, we have not discussed that, this is one of the major weaknesses.

1.7. Searching process

For this research article, this comprehensive analysis gathered a noteworthy 415 papers from Elsevier accessed from https://www.elsevier.com, Google Scholar accessed from https://www.scholar.google.com, and Science Direct accessed from https://www.sciencedirect.com Even then, we decided to leave some of the research repositories as Research Gate, and Academia.edu out because recent research analysis suggests that it seems unable to compete with Google Scholar in the aim of giving early citation indicators [77,78].

In this work, the following process is written in the proper structure: Section 2 describes the background study of the root cause of different plant leaf diseases and research articles summary associated with leaf disease which has been successfully compiled from June 2010 and December 2022. Section 3 digs deeper into the methodology into the basic steps, including the disease detection workflow, that has been chosen in many kinds of literature broadly. Discussion is placed in Section 4. The fifth segment involves application challenges and problems related to leaf disease detection. The work's conclusion and potential vision are presented in the final Section 6.

2. Background study

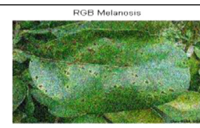
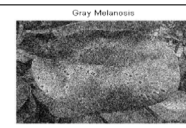
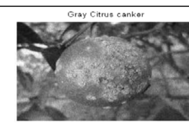
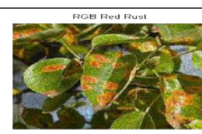
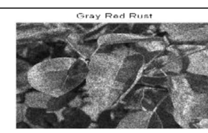
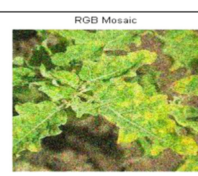
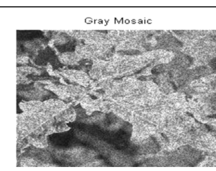
Root causes of different leaf disorders, all collected leaf images in previous research works and literature surveys related to leaf disease are discussing points of this section. These points provide all the information of previous studies, which have been illustrated in paragraph and tabular manner for easier understanding.

In a broad sense, Table 1 covers many diseases, their source plants, causative agent, and symptoms. This research study reviewed various kinds of literature and compiled various leaf diseases using a combination of several methodologies with their generalization measures as shown in Table 2. Table 3 represents relevant information about the considered images. Overall, Table 4 gives a summary of previous research on ML and DL in the field of leaf disease detection, including common steps such as pre-processing, segmentation, feature extraction, classification, recognition, and their measures. Moreover, Table 5 and Table 6 are having details about the measures of, effectiveness that the researchers used in their research experiments, respectively. Table 7 indicates lists of repositories available for the leaf disease datasets.

2.1. Root cause of different plant leaf disorders

Plant malady is one kind of trouble that can impede the normal functioning of a plant due to various causative agents like pathogens, infectious organisms, and environmental conditions. According to the literature and research study, plant leaf disease is primarily caused by bacteria, fungi, and viruses, as well as similar other causes, like insects, pests, and mites. There are different symptoms of these causes and the treatment of these diseases also varied. So, to understand the crucial thing of this issue, early detection of these diseases is very necessary to restrain leaf loss.

Table 1
Different kinds of noises in red-green-blue (RGB) images and Gray level images.

S. No	Noise Type	Symptom of Noise	Noisy infected Images (RGB)	Noisy infected Images (Gray)
1.	Salt & Pepper (variance = 0.3)	It creates black and white spots on the image of infected leaves in the case of RGB mode and gray-level images. That is why infected portions cannot be visible clearly.		
2.	Gaussian Noise (mean=0, variance = 0.025)	It affects both the dark and light areas of an image. For gray level images observation of the infected area is critical.		
3.	Poisson Noise	This noise manifests as a random structure in an image. The presence of this kind of noise does not hamper so much in this research study		
4.	Speckle Noise	It changes the gray levels of an image. Finding the stressed areas in the case of the gray level image is not a simple task.		
5.	Localvar Noise	This is Gaussian white noise of local variance. For this noise, the image becomes hazy so how many areas are infected cannot be understood perfectly.		

The symptoms of these diseases, which are caused by bacteria, fungi, and viruses, are listed in Table 2.

- ***Bacteria:*** Bacterial diseases are caused by rain, wind, insects, and birds. Various types of symptoms like leaf spots, soft rots, scabs, and cankers can be visible for this organism. They grow on the surface of the leaf and create an infection in leaf tissues. The spread of bacteria which must be prevented instead of curing the leaf can be considered to control bacterial diseases. Fig. 1(a) indicates that citrus fruit is affected by a bacterial disease and Fig. 1(b) represents the classification of bacterial diseases [232].
- ***Virus:*** The presence of a virus in an infected leaf is difficult due to its small size. These organisms need a living host to grow up and then the virus creates a protein coat and moves from one cell to another. Sometimes a leaf can be infected with the virus without any symptoms. Potato mop-top, sugar beet curly top, lettuce mosaic, maize dwarf mosaic, potato leaf roll, and peach yellow bud mosaic are the names of viruses. Fig. 2(a) displays infected red bell pepper caused by a viral disease whereas Fig. 2(b)shows the classification of viral diseases [166,233,234].
- ***Fungi:*** Fungi generally consume energy from infected leaves and damage those leaves by creating scabs, rust, and rotting tissues. Rust, powdery mildew, and downy mildew are the names of fungi whose symptoms can often be seen on infected leaves, vegetables, flowers, and fruits. An infected portion of the leaf is usually cut off from the whole plant to

(a) (b)

Fig. 2. (a): The virally infected bell paper, (b): Classification of virus-based disease.

(a) (b)

Fig. 3. (a): The fungus-infected flower, (b): Classification of fungal-based disease.

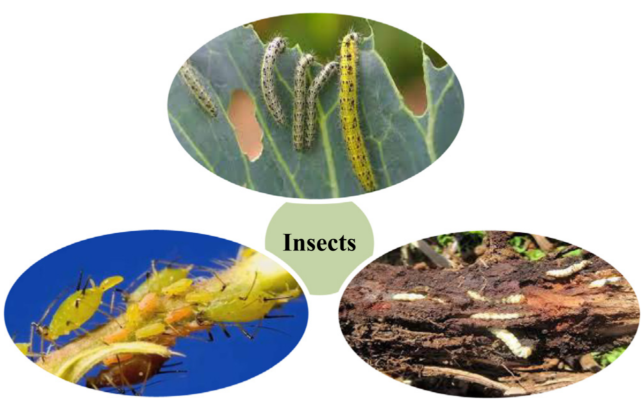


Fig. 4. (a-c): Stem-chewing insects, Root-chewing insects, and sucking insects.

prevent the spread of infection. Sometimes an infected leaf can be benefitted from excessive watering. Fig. 3(a) displays the condition of the infected flower with the fungus organism and Fig. 3(b) shows different kinds of fungal diseases [235].

- ***Pest:*** Pest is another kind of agent that causes a problem in a life cycle of a plant. Insects can be differentiated by their one pair of antennae, some legs, and wins [236]. Most insects spend their lives in the plant in order to obtain food, and as a result, the plant suffers. Bees, whiteflies, aphids, mealybugs, spiders, and ants are just a few examples of those who feed on plant cell contents [237]. Based on the areas of the plant that are impacted by pests, three categories of pests can be identified. Chewing insects such as weevils, bigger caterpillars, grasshoppers, and katydids chew on leaves, causing them to become irregular in shape. Long-horned beetles (Round-headed borers), metallic wood-boring beetles (flathead borers), engraver beetles, clearwing moths, American plum borer (a moth), and a few less usually observed moths are examples of stem chewing insects [217]. Root chewing insects such as root weevils and root maggots gather nourishment from the roots and eat a mix of soil organic materials and roots [238]. Sucking insects such as aphids, leafhoppers, scales remove sap from plants thereby they weaken the plant. Thus, it kills the plant. They also support the growth of sooty mold as a result plant becomes infested with pests as well as bacterial or fungal or viral organisms. Enough fertilizer, particularly in the growing season can protect the plant from these unwanted agents. The resistant plant material can be considered an ideal method to reduce pest populations [237]. Fig. 4(a) displays the stem-chewing insect [236], Fig. 4(b)shows root-chewing insects [239] and 4(c) shows sucking insects [240].

2.2. Information about the collected images

See Table 3.

2.3. Literature survey related to leaf disease

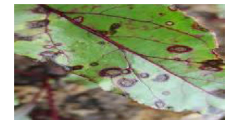
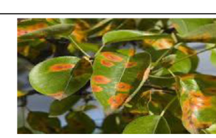
This section examined various research publications published between June 2010 and December 2022 and provided a comparative analysis for the recognition of leaf disease in a variety of plants. Here, we tabulate the various features and attributes such as the research article's author's name, plant and tree organisms, diseases associated with them, the image pre-processing method used, segmentation method used, feature

Table 2
Summary of different leaf diseases caused by fungi, bacteria, viruses, and pests.

Disease	Plant/Tree Name	Causative Agent	Symptoms	Image of Infected Plant
Black Sigatoka [79–81]	Banana	Fungi	1. Black and yellow streaks with tiny chlorotic spots appear on the bottom surface of the 3rd or 4th open leaf. Streaks of leaf become darker. 2. Sometimes purple tinge can be visible on the top surface. Large areas of the leaf become blackened water-soaked.	
Black spot/ Black speckle [82,83]	Rose, Apple, Grape, Papaya, Cucumber, Pomegranate	Fungi/ Bacteria	1. Yellow areas are surrounded by spots that expand to cover the entire leaf. 2. Round leaf spots with irregular, feathered margins are another sign of this disease.	
Sooty mold [84,85]	Azaleas, Gardenias, Camellias, Crepe myrtles, Mangifera, Laurels	Fungi	1. Black mats and a velvety growth or a dark crust can be seen on living leaves and smaller twigs.	
Anthracnose [86,87]	Ash, Oak, Annuals, Sycamore, Maple grasses, Mango, Papaya, Cucumber, Strawberry, Pomegranate	Fungi	1. Several small tans to brown dots appear on the leaves. 2. Small, yellowish watery spots enlarge rapidly to become brownish.	
Botrytis blight/ Rot/ Gray mold [88,89]	Sunflower, Apples, Pears, Peaches, Plums, Raspberries, Strawberries, Blackberries, Tomato, Cucumber	Fungi	1. Sunken brown spots can be visible on the back surface of the head. 2. Initially botrytis may form small, black sclerotia within the sunflower head.	
Downy mildew [90,91]	Sunflower, Grapes, Soybeans, Cucumber	Fungi	1. Root and leaf become infected. 2. Infected leaves contain chlorosis on the upper surface and white sporulation on the bottom surface.	

(continued on next page)

Table 2 (*continued*).

Cercospora leaf spot/ White leaf spot ([92,93])	Grain legume, Carrot, Eggplant, Pepper, Alfalfa Oil, Tomato, Tobacco, Rice, Corn, Sorghum, Palm, Cotton, Coffee, Sugar Beet, Grape	Fungi	1. Initially, white spots can be visible on the leaves. 2. Light gray to dark tan with a brown to purple border can be also seen on leaves. 3. Infection can be shown on older leaves and gradually it spreads to newer leaves.	
Scab [94,95]	Apples, Crab-apples, Cereals, Cucumbers, Peaches, Pecans, Potato	Fungi/ Bacteria	1. Affected leaves become wither. 2. Brown spots or lesions can appear on the surface of the root and damage the root.	
Blast [96,97]	Rice	Fungi	1. In rice seedlings, little necrotic patches first emerge, then get larger, consolidate, and have chlorotic edges. 2. In older plants, symptoms appear in the leaves, collar-junction of the leaf blade, leaf sheath, nodes, neck, and panicle.	
Stripe blight [98,99]	Oats, Rice, Wheat	Bacteria	1. Symptoms include water-soaked and red-brown longitudinal bands with narrow yellow edges. 2. Stripes combine to form blotches, which force the leaf to fall.	
Sheath blight [100,101]	Rice, Maize,	Fungi	1. Green-Gray and water-soaked, are found on the lower leaves of rice. 2. Leaves become tan with a brown border when the sun penetrates and then lesions become dried.	
Mosaic [102,103]	Tobacco, Cassava, Beet, Cucumber, Alfalfa, Sunflower	Virus	1. Mild mosaic pattern appears on leaves of young plants. 2. Irregular leaf mottling appears, with light and dark green or yellow spots, and the plant shrinks.	
Red rust/ Rust ([104,105]; [106])	Roses, Hollyhocks, Tea, Snapdragons, Daylilies, Beans, Tomatoes, Lawns, Wheat, Alfalfa, Almond, Beet	Fungi	1. Initially spots are yellow then spots become black. 2. Black spores are visible on leaves, stems.	

(*continued on next page*)

Table 2 (*continued*).

Granville wilt ([107,108])	Tobacco, Tomato, Potato, Eggplant, Pepper	Bacteria	1. Rapid yellowing, stunting, wilting of the leaf. 2. Brown to black spots take place on the stalk and are finally killed by this disease.	
Alternia rot ([109])	Apple, Cotton, African daisy-plant, Beet, Chickpea, Lemon	Fungi	1. Lesions are round, dry, hard, and shallow, with dark, olive green, and black surfaces. 2. The disease typically develops near insect feeding injuries.	
Late blight (Phytophthora blight) ([110,111])	Potato, Tomato	Fungi	1. Water-soaked spots in light and dark green, circular and irregular shapes can also be seen on leaves. 2. These lesions first appear on lower leaves (leaf tips) gradually spots spread to upper leaves.	
Powdery mildew (Sphaerotheca-fuliginea) [112,113]	Mustard, Mint, Cucumber, Wheat, Sugar beet, Sunflower, Grape, Peach, Strawberry, Tomato, Alfalfa, Almond, Rubber	Fungi	1. Circular to irregular patches can be visible on both sides of leaves which become dusty, powdery, Grayish brown.	
Early blight ([114,115])	Potato, Tomato, Apple, Eggplant	Fungi	1. On diseased leaves, brown-colored spherical points develop. 2 Dry brown spots with dark brown concentric rings can be found on infected stems of older plants. 3. Fruit spots are leathery, black, and infected fruits may drop.	
Citrus canker ([116,117])	Tomato, Lemon, Orange, Grape, Rose	Fungi/ Bacteria	1. The lesion can be seen on leaves, fruits, twigs, branches. 2. At first, little, watery, spherical spots appear on the lower surface of the leaf, then fade to yellowish-brown colour.	
Melanosis ([118,119])	Lemon, Orange, Grape	Fungi	1. Small black specks appear on leaves and leaves become distorted.	

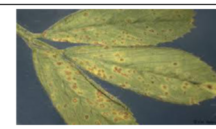
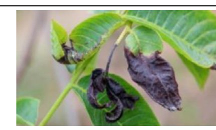
(*continued on next page*)

Table 2 (*continued*).

Brown Rot ([120,121])	Pineapple, Almonds, Apricots, Cherries, Peaches, Plum	Fungi	1. Blossoms are infected first in spring. 2. Flower-bearing stems are killed. 3. Circular or brown spots can be seen in mature fruits also.	
Frogeye leaf spot [122,123]	Soybean	Fungi	1. Initially, dark water-soaked patches emerge on leaves, which turn brown over time.	
Leaf spot ([124,125])	Papaya, Peanut, Pineapple, Mango, Maize, Hazelnut, Banana, Cranberries, Carrot, Cotton, Coconut, Sugar beet	Fungi	1. Spots appear on the foliage. 2. Spots can be brownish, tan or black, or dark margin. 3. Leaves may drop.	
Early scorch [126]	Oak, Banana	Bacteria	1. The first symptom of spots can be visible on leaves, gradually it spreads to the other parts of plants. 2. Yellow or red band spots are shown on irregularly shaped leaves.	
Smut ([20,21,127–129])	Wheat, Maize, Sugarcane, Grasses, Barely, Potato, Rice (Smut kernel, False smut)	Fungi	1. Infected seedlings may die within six weeks. 2. Infection becomes spreads leaves to leaves. 3. Blister-like lesions can curve the leaf downward.	
Scald ([130]; Scal, 2021)	Barely, Sugarcane	Fungi	1. Leaves become oval, water soaked, Gray, and green. 2. Gradually symptoms become light Gray, dark brown margin.	
Stackburn ([131])	Rice, Wheat, Maize	Fungi	1. Spots can be brown to the white and darker border.	

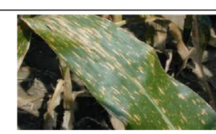
(*continued on next page*)

Table 2 (*continued*).

Whitetip ([132,133])	Onion, Rice, Wheat	Virus	1. Initially infection occurs at the leaf tip and less frequently between the leaf tip and mid tip 2. This inptosphaerulina leaf spofection appears as a water-soaked-like spot and then spread to a lesion.	
Leptosphaerulina leaf spot [134,135]	Alfalfa, Grasses, Soybean, Peanut, White clover	Fungi	1. Leaves die back from their tips. 2. Leaves, a sheath may contain yellow, brown lesions and water-soaked spots.	
Taphrina deformans (Leaf curl) ([136,137])	Peach, Almond, Nectarine	Fungi	1. Reddish areas develop on leaves and become thick. 2. It can reduce fruit production.	
Erwinia amylovora (Fire blight) [138,139]	Apple, Pear, Crab-apple, Raspberry	Bacteria	1. These bacteria affect blossoms, fruits, shoots, and branches of apples, and pears. 2. Infected tissues of blossoms and young fruits become black and die. 3. Young twigs and brunches die from the terminal.	
Venturia (Apple Scab) [140,141]	Common pear-firethorn, Mountain ash-apples, Ornamental crab-apples	Fungi	Infection occurs on leaves, fruit, flowers, and young green shoots. Large scab-like lesions can warp the leaf's shape. Young fruit is often infected by foliar conidia. Brown corky spots appear on leaves, fruits, and young fruits untimely drop. Mature fruits contain small, black 'pin-head scabs'	
Gymnospo-rangiumsabinae (Pearrust, European pear rust) [142,143]	Pear	Fungi	1. On young fruits and twigs, yellowish-orange leaf dots are apparent at first. 2. Leaf spots turn a vivid reddish orange color in the summer, and tiny black dots form in the center of the spots in the middle of the summer.	

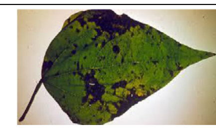
(*continued on next page*)

Table 2 (*continued*).

Phaeosphaeria spot [144,145]	Maize, Nutshell	Fungi	1. Initially small, pale green to yellow chlorotic dots are scattered over the leaf blade. 2. These spots later enlarge; become circular and dark brown irregular margins.	
Target spot [146–148]	Cowpea, Cucumber, Papaya, Rubber, Soybean, Tomato, Cotton, Tobacco	Fungi	1. Infected leaves contain tiny lesions which enlarge into light brown lesions with distinct yellow halos. 2. That is why infected tissues become collapsed.	
Bacterial wilt ([148,149])	Cucumber, Muskmelon, Squash [150], Pumpkins	Bacteria	1. It blocks the water transport system of a plant. 2. Sticky milky color layer can be visible over infected leaves. 3. Infection spreads and infects the whole plant and the plant dies.	
Black rot/Black stem, Black vein, Stem rot, and Stump rot ([151,152])	Apple, Cauliflower, Cranberries, Carrot, Mango, Mustard, Papaya, Potato, Tea	Fungi/ Bacteria	1. Plant is infected during its growth stage. 2. Infected seedlings become yellow, and lower leaves of seedling are dropped finally, may die. 3. Blackened veins appear in stems and cauliflower curds become infected and turn brown.	
Gray leaf spot [153–155]	Maize, Grasses, Mango, Pepper, Tea, Tomato	Fungi	1. In the early stage of infection leaves contain small, spherical lesions with a yellow halo around them and initially, it looks like eyespot, common rust. 2. Gradually lesions are merged and kill the entire leaf.	
Eyespot ([156,157])	Wheat, Corn, Sugarcane, Rice, Barely	Fungi	1. In the center, yellow eye-shaped elliptical lesions with black pupil-like specks emerge, surrounded by greenish, brown to dark brown bands.	

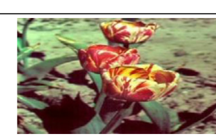
(*continued on next page*)

Table 2 (*continued*).

Septoria leaf spot ([158,158])	Tomato, Banana, Barely, Citrus	Fungi	1. Sports are circular with dark brown margins. 2. Infected leaves turn yellow, then brown, and eventually wither.	
Black chaff/Bacterial leaf streak ([159,160])	Wheat, Rice	Bacteria	1. Initially translucent water-soaked streaks appear on the leaves. 2. After a few days, lesions are covered by a lime green halo and spots turn brown. 3. Shape of lesion irregular and gradually they spread to the entire surface of a leaf.	
Angular leaf spotorisariopsis leaf spot ([161,162])	Cucumber, Papaya, Tobacco, Strawberry, Beans	Bacteria	1. Leaves, fruits, and stems are affected. 2. Spot is irregular with a water-soaked appearance and the shape of the spots is angular. 3. The water-soaked area later turns Gray and dies. 4. Water-soaked spots are smaller and more circular on fruits than on leaves.	
Rhizopus rot ([163])	Grape, Sunflower, Sweet potato, Jackfruit, Pumpkin, Strawberry, Apricot fruit, Citrus, Peach	Fungi	1. This type of infection can be seen in the wounded area and gradually it spreads over and decays the fruits or flowers. 2. Light brown water-soaked lesion appears on fruits.	
Sunscald [164,165]	Barks, Fruit	Sun	1. Sunscald symptoms appear when the fruit is exposed to direct sunlight after being in the shadow for an extended period of time, resulting in mortality from insects, animals, germs, or fungi. This sunscald is doing havoc on fruits and vegetables.	
Frost Crack/ Southwest canker ([166])	Barks	Sun	1. Weakness in barks (mature oaks, pine, poplars) causes this type of problem. 2. In winter temperature of trees drop quickly with an insufficient amount of sunlight. That time barks open in a long crack.	

(continued on next page)

Table 2 (*continued*).

Pink disease [167,168]	Teak, Breadfruit/ Jackfruit, Carambola, Citrus, Custard apple, Durian, Mango, Pineapple	Fungi	1. This disease produces stem canker. 2. Infected bark and branches of the tree are split and cracked. The fungus penetrates intact wounded bark and gradually kills the cambial layer. 3. So larger branches and trees can be killed by this disease.	
Southern corn leaf blight [169,170]	Maize	Fungi	1. Initially diamond-shaped spots are small. 2. Then spots are larger and rectangular. 3. Lesions have a red to dark brown border.	
Northern corn leaf blight [154,155,171]	Maize	Fungi	1. The lesions are canoe-shaped and initially bordered with a Gray-green margin. 2. Then it turns tan-colored.	
Curvularia leaf spot [172–174]	Maize	Fungi	1. A little, tan-colored lesion with a brown edge is encircled by a yellowish halo on the leaves.	
Cucumber green mottle mosaic virus ([175,176])	Watermelon, Cucumber, Zucchini, Pumpkin, Squash, Bitter gourd, Bottle gourd, long melon	Virus	1. The virus affects the young leaves with green, light green, yellow-green spots. 2. Activity of this virus can be shown for young leaves. 3. Infected fruit can be dropped.	
Tobacco mosaic virus ([177])	Tobacco, Tomato, Pepper	Virus	1. The first symptom is light green spots that appear between veins of the young leaves. 2. Infected leaves display wrinkles but this infectious does not responsible for plant death.	
Tulip breaking virus [178]	Tulip	Virus	1. This virus breaks the color of the tulip flower by locking a single color. 2. This symptom depends on the plant variety and age. 3. Infected plants produce distorted leaves and flowers.	

(*continued on next page*)

Table 2 (*continued*).

Cauliflower Mosaic virus ([179,180])	Cauliflower	Virus	1. Necrotic lesions appear on the leaf surface. 2. Overall structures of infected plants become deformed. 3. Another symptom is the stunted growth of infected plants.	
Potato Virus Y ([181])	Potato, Tomato, Tobacco, Pepper	Virus	1. Infected leaves become yellow and moulted. 2. This infection causes the problem of stunting. 3. Sometimes leaves become crinkled for this disease.	
Esca (Grapevine leaf-stripe) ([182,183])	Grape, Berries	Fungi	1. Type of grapevine trunk disease, occurs during the growing season. The main symptom is striping on leaves that can be characterized by discoloration, and drying of the tissues around the main veins with dark red and yellow. Leaves can dry out and drop untimely.	
Bitter rot/ Blossom end rot ([184,185])	Apple, Mango, Chestnut, Pear	Fungi	1. This is a common fruit rotting disease. The first symptom is small circular light to dark brown dots on fruits. 2. On mature fruits the infected area is surrounded by a red halo and gradually they cover the whole area of fruit.	
Cottony rot/ Cottony mold/ White rot ([186,187])	Beans, Carrots, Celery, Lettuce, Bush bean	Fungi	1. As the initial indicator, infected sections turn white, and pale to dark brown coups appear on the stem at the soil line. 2. Other symptoms, such as wilting and leaf loss, emerge on the plant's upper half, and death is imminent. On the fruit tissue that meets the dirt, dark lesions emerge initially.	
Bacterial blight ([188,189])	Pomegranate	Bacteria	1. Initially yellowish water-soaked circular spots can be found on fruits and leaves. 2. Then this spot or lesion becomes irregular, and they can crack the infected fruits and fruits become dark and dry.	

(*continued on next page*)

Table 2 (*continued*).

Early leaf spot ([190,191])	Groundnut	Fungi	The upper side of plants contains reddish-brown spots which are surrounded by a yellow halo and brown spots are visible on the lower surface.	
Late leaf spot ([190–192])	Groundnut	Fungi	1. It generates brown to dark circular patches that are not encircled by a golden halo. 2. On the lower surface of diseased leaves, concentric circular dots form.	
Rust (Puccinia arachidic) ([193,194])	Groundnut	Fungi	1. Six weeks old plants are infected with this disease and small brown to chestnut dusty pustules appear on the lower surface. 2. The severely infected plants may produce small and shriveled seeds.	
Bud necrosis virus ([195]; Bud necrosis virus, 2021)	Groundnut	Fungi	1. Ring spots can be seen on leaves in 2-6 weeks. 2. Newly emerged leaves become small and irregular-shaped lesions are visible on the infected leaves.	
Alterniaarchidis ([196]; Alterniaarchidis, 2021)	Groundnut	Fungi	1. It produces small brown, irregular-shaped spots which are surrounded by yellow halo spots. 2. Gradually infected areas become dry out and disintegrate.	
Stemphylium ([197,198])	Spinach	Fungi	1. Leaf spots begin as little circular to oval gray-green spots. 2. Gradually those spots become tan and older spots dry up.	
Coffee leaf rust ([199,200])	Coffee	Fungi	Small yellowish, oily spots occur first on the upper surface of diseased leaves, subsequently, these small spots darken with a yellow border.	
Coffeeberry disease ([201,202])	Coffee	Fungi	Dark necrosis can be seen on coffee berry and infected berries drop prematurely.	

(*continued on next page*)

Table 2 (*continued*).

Coffee wilt disease ([203,204])	Coffee	Fungi	1. Internal symptom includes a water flowing problem in the whole body of an infected plant. 2. Leaves lose moisture as an external symptom and become discolored. 3. Mature trees are cracked, and plants become dead.	
Cedar apple rust (Cedar apple rust, 2021; [205,206])	Apple, Crab-apple	Fungi	1. Leaf spots start yellow and then turn brilliant orange red, with a bright red border. 2. This disease causes green to brown irregular patches with black dots to appear on the fruit surface. 3. There are small black dots amid leaf spots on the upper leaf surface of mature leaves.	
Black rot ([178,179,207–209])	Grape	Fungi	1. Brown circular lesions can be seen on infected fruits. 2. Within a few days fruiting bodies are damaged	
Tan spot ([210,211])	Wheat, barley, rye	Fungi	1. Tan colored with a surrounding yellow halo and a dark spot diamond or oval-shaped lesions can be visible in the center. 2. An ample number of lesions kill leaf tissues.	
Peacock spot [212]	Olive	Fungi	1. Small sooty blotches develop on leaves and those blotches are changed into greenish-black circular spots. 2. As diseases develop the leaves become yellow and fall.	
Aphids [213]	Cannabis	Pest	1. It affects the leaves of cannabis with its harmful fluids. 2. It creates white skin moults. 3. The growth of leaves becomes slow and yellowing.	
Spider mites (Spider mites, 2021)	Plants	Pest	1. Infected leaves look Gray or light bronze. 2. A bad ingestion can seriously damage leaves and plants.	

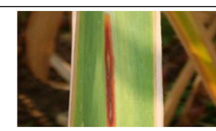
(*continued on next page*)

Table 2 (*continued*).

Bud's mite and blister mite ([214,215])	Grape	Pest	1. Bud's mites feed on and damage young buds. 2. Blister mites cause galls on leaves.	
Whitefly ([216])	Tomatoes, cabbage, peppers, eggplant, strawberries, cucumbers, pumpkin, okra, sweet potato, etc.	Pest	1. Affected leaves become yellow and wilt. 2. They help to spread the tomato yellow curl virus. So, plants become weakened.	
Mealybugs ([217])	Plants	Pest	1. They affect many flowerings and houseplants by direct feeding and by introducing diseases. So, the leaves look wrinkled. 2. Leaves become yellow, and wilt. An ample number of mealybugs kill a plant.	
Leaf miners [218]	Tomato	Pest	1. Repeated infestation could stress and weaken leaves. 2. Severe attack of this pest can kill a plant.	
Scale insects [219]	Citrus plants	Pest	1. Plant roots, bark, leaves, twigs, and fruits may be attacked by these insects.	
Citrus leaf miner ([220])	Citrus plants	Parasite	1. In its larval phase it presents in leaves, and it traces a sinuous gallery in its path. As a result, leaves are rolled, and dried.	
Tiny whiteness ([221])	Holy, lemon, Thai, or Genovese — basil plants	Fungi or insects	1. Insects such as aphids, thrips, leafhoppers, spider mites, whiteflies, and mealybugs. feed on leaves and create spots. 2. Fungal diseases create small splotches that gradually cover the entire leaf surface.	
Berry disease [222]	Strawberry	Fungi	1. For infection, the seeds of this fruit become black. That is black seed.	

(*continued on next page*)

Table 2 (*continued*).

Foot rot/quick wilt ([223–225])	Black pepper	Fungi	1. Rainy reasons mainly from October to November are favorable for developing this disease. 2. For this pathogenic bacterium, the major stem at ground level, or collar, is injured. The branches fall off at nodes within a month, and the entire vine collapses.	
Solar scorch/Leaf scorch [226]	Shrub and herbaceous plants	Sun	1. Leaves become dry, turn brown and become brittle due to windy or sunny weather as roots are unable to supply water to foliage.	
Citrus greening [227]	Citrus plants	Bacteria	1. Initially, veins and adjacent tissues of leaves become yellow. 2. Symptoms of the disease include premature defoliation, twig dieback, feeder rootlet, lateral root degradation, and a loss in vigour, all of which result in the death of the entire plant.	
Red rot [228]	Sugarcane	Fungi	1. Affected sugarcane leaves become changed from green to red. Then these leaves start drying from bottom to top. 2. The split opened cane shows, the inner region is reddish with intermittent white tinges across the cane length.	
Bean pod mottle [229]	Soybean	Virus	1. Symptoms appear mostly on young leaves. 2. Leaves become distorted, and wrinkled. As a result, a mottled color pattern can be visible on them.	
Sugarcane mosaic virus [230]	Sugarcane	Virus	1. Infected green leaves are surrounded by paler green.	
Brown spot [231]	Apple/ berry	Fungi	1. Irregular brown and black spots can be visible on infected leaves in early spring. 2. Infected shoots become black and weaken.	

extraction process utilized, classification techniques used, performance measures considered, recognition parameters and so on as shown in Table 4, respectively. We also looked at a variety of feature extraction, feature selection, data annotations, and segmentation metrics as well as various performance indicators that have been used in several studies effectively. Fig. 5 provides the list of journal papers that discussed leaf disease detection using AI, from June 2010 to December 2022. There are many articles available on this research study that have been adopted by the university, private organizations (Pvt. Org.), government

Table 3
Information about collected images of infected leaves.

S. No.	Infected Leaf Image	Description
1.	Black Sigatoka	Photographs taken on 2016-03-25, CC-Zero, Items with OTRS permission confirmed, P6305 SDC, Photographs by Scot Nelson, Taken with Sony DSC-RX100 III
2.	Sooty mold	Photographer: Joseph Obrien, Organization: USDA Forest Service, Descriptor: Sign, Description: Cladosporium, Aureobasidium, Antennariella, Limacinula, Scorias, and Capnodium and other species of fungi cause sooty mold on a variety of hosts, Image type: Field, Host: California laurel (Umbellularia californica (Hook. & Arn.) Nutt.)
3.	Early leaf spot	Contributor: Nigel Cattlin/ Alamy Stock Photo, Image ID: 2C1D9F4, File size: 59.3 MB (2.1 MB Compressed download), Dimensions: 5217 $\times$3972 px | 44.2 $\times$ 33.6 cm | 17.4 $\times$ 13.2 inches | 300dpi, Photographer: Nigel Cattlin,
4.	Brown spot	Photographer: The Spruce/ K. Dave, Photography is taken on 2021-10-20, Host:'the spruce Make your best home' Image type: Field.
5.	Bean pod mottle	Photographer: Edward Sikora, Organization: Auburn University, Image type: Field, Host: soybean (Glycine max (L.) Merr.), Image Number: 5581650, Image location: United States, Alabama, Limestone County.

organizations (Govt. Org.), industry, and collaboration between a university and private (U&P) organizations. Most of the universities have selected primitive together with recently implemented ML and DL models for their purposes. Government organizations, private organizations, and industries also have funded research work. The motivation of most of these organizations is to apply all these models in agribusiness fields for providing the easiest and most efficient process of leaf disease recognition to a farmer.

Fig. 6 indicates the relation between name of countries versus number of articles and Fig. 7 represents the performance of listed ML-based such as SVM, TSVM, RF, DT, ANN, KNN, logistic regression (LR), linear discriminant analysis (LDA), radial basis kernel function (RBF), multilayer perceptron (MLP), back propagation neural network (BPNN), and DL-based algorithms such as CNN, deep convolutional neural network (DCNN), densenet (DNet), VGG16, LeafNet (LN), convolutional encoder network (CEN), ResNet (RNet), EfficientNet (ENet), Gabor Capsule Network (GCN), Learning Vector Quantization (LVQ), LeNet (LNet), Extremely Randomized Tree (ERT) and AXGBoost (AXGB) and other models such as BRBFNN, BP-ANN, updated CNN, Synthetic Minority Oversampling Technique, deep CNN [53], delta tributary network, Extreme Gradient Boosting or XGBoost, GoogLeNet, Inception v3, PLSR, NNE, RBPNN, faster R-CNN, SVM, adaptive OCM (template), Spectral vegetation indices using hyperspectral imaging data, SCANet, AlexNet, DCNN with Nesterov's accelerated gradient (NAG), CNN trained using segmented images (S-CNN), CNN trained using full images FCNN, double region proposal network with Inception module and attention structure (DR-IACNN), VGG-FCN-VD16, VGG-FCN-S, GoogLeNet inception structure with rainbow concatenation, KSTAR, depth-wise separable convolutional PLD have been considered for this survey from June 2010 to December 2022.

Fig. 7 in the form of a line chart illustrates the performance of those models and adopted those models in the research field using the accuracy performance parameter. The outcome of this figure specially mentions the SVM algorithm that has been applied mostly in the research work on leaf disease detection. Besides this model random forest, CNN, and ResNet has been used frequently.

2.3.1. Analysis of agriculture productions in different organizations by using current technology

There are many articles available on this research study that have been adopted by the university, private organizations (Pvt. Org.), government organizations (Govt. Org.), industry, and collaboration between a university and private (U&P) organizations. Most of the universities have selected primitive together with recently implemented ML and DL models for their purposes. Government organizations, private organizations, and industries also have funded research work. The motivation of these organizations is to apply all these models in agribusiness fields for providing the easiest and most efficient process of leaf disease recognition to a farmer.

Industry 4.0 refers to the fourth industrial revolution, which is characterized by the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, robotics, and cloud computing into manufacturing processes. Digital transformation, on the other hand, refers to the process of using digital technologies to fundamentally change the way businesses operate and deliver value to customers. Digital transformation involves leveraging advanced technologies such as the cloud, AI, machine learning, and big data analytics to improve plant leaf detection efficiency and drive growth in the agriculture sector. Overall, in leaf disease detection, Industry 4.0 and digital transformation are both focused on harnessing the power of advanced technologies to drive innovation and improve the efficiency of leaf disease detection. Basically, the Industry 4.0 digital transformation helps in production and value creation processes. This could be a possible reason for a signifi-

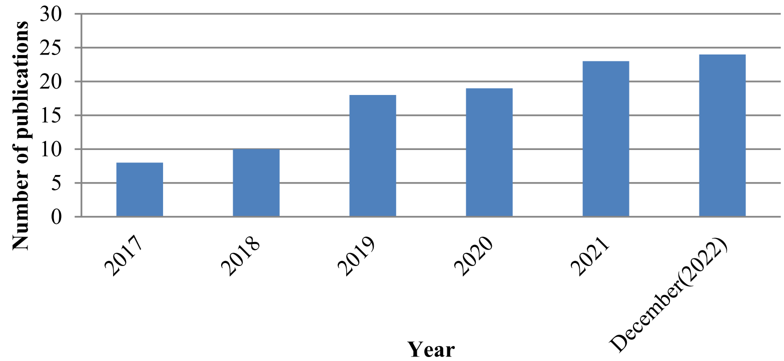


Fig. 5. Number of published Journal articles related to leaf disease detection for the year of publication to the best of gathered knowledge.

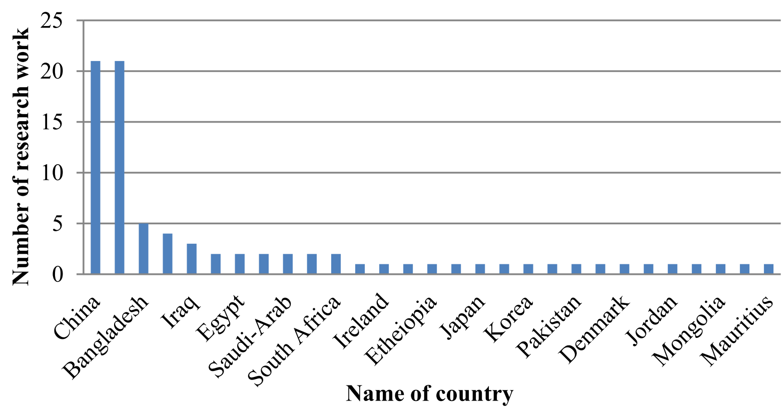


Fig. 6. Number of research works from various countries for leaf disease detection.

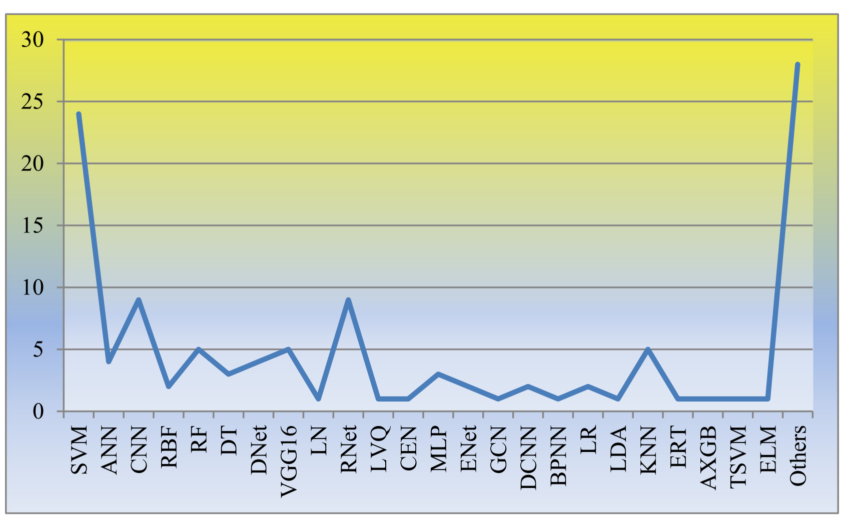


Fig. 7. Line chart related to applicable models for leaf disease detection from June 2010 to December 2022.

cant increase in research since 2017. Fig. 9 shows various ML and DL based methods that have been adopted by industries, government organizations, private organizations, university and collaborations.

Notations. $m \times m$ denotes the size of the co-occurrence matrix, $m = 1, 2, \ldots$ and p_{ij} is the quotient of the element (i, j) of the co-occurrence matrix divided by the sum of the elements of this matrix; S and L represent the area and perimeter of a lesion, respectively; $\mu_j|(j = 1, 2, 3)$ represents first, second and third moments respectively; f_i is a random variable of Gray level and $p(f_i)$ represents the Gray level histogram of an image region for $i = 0, 1, 2, \ldots, L - 1$ where L is the number of different Gray levels; $N =$ the number of populations or data points; $x_i =$ each value from the population; μ = population mean ; $P_+ =$ fraction of positive example in the sample; $P_- =$ the fraction of negative example in the sample; $P_d =$ normalized metrics dimension of GLCM; R =red; $G =$ green; $B =$ blue; $S^4 =$ a sum of deviation scores in fourth power; $Y_i =$ univariate data or random variables; $n =$ the number of data points; $X_i =$ independent random variables, $j =$ number of Gray levels in the image, $G =$ GLCM mean; $P_{ij} =$ element ij of the normalized symmetrical GLCM, $N_g =$ total number of intensity levels, $P(i, j, 1, 0) =$ intensity of co-occurrence matrix, $f(x, y) =$ binary image function, $LA =$ lesion

Table 4
Summary of leaf disease detection techniques surveyed from a list of publications in various indexed journals from June 2010 to December 2022.

Models	Plant/Tree	Diseases	Image Pre-processing	Segmentation	Feature Extraction	Performance Parameters	Recognition Parameters (%)	Authors
ANN	Cotton	Early scorch, Cottony mold, Ashen mold, Late scorch and Tiny witness	RGB to HSI images	K-means clustering	Color co-occurrence methodology (CCM)	Accuracy	93	Al Bashish et al. [19]
	Brinjal Leaves [241]	Bacterial Wilt, Cercospora Leaf Spot, Tobacco mosaic virus					85–95	R et al. (2016)
	Strawberry	Powdery Mildew	–	–			87.65	Mahmud et al. [242]
	Man-goLeaves	Anthracnose, Gall Midge, Powdery Mildew, and Healthy	Resized to 256 × 256	–	Adaptive Particle – Gray Wolf Optimization (APGWO)		91.32	Pham et al. [24]
BPNN	Wheat, Grape	Wheat stripe rust, Wheat leaf rust, Grape powdery mildew, Grape downy mildew	Image resized. *Wheat* 2592 × 1944 to 400 × 300 pixels *Grape* 2592 × 1944 to 800 × 600 pixels Median filter to remove noise	K-means clustering	PCA		*Wheat* Prediction-100 Fitting-100 *Grape* Prediction-97.14 Fitting-100	Wang et al. [20,21]
	Vegetable crop	Early blight (EB), Late blight, and Powdery mildew	Applied median filter to remove noise	K-means based on a set of Features L*a*b (L* represents lightness from black to white, a* indicates green as the negative direction to red as the positive direction and b* indicates blue as the negative direction to yellow as positive direction conversion.)	Color moments, gray level co Occurrence matrix (GLCM)		95.3	El Massi et al. [243]

(*continued on next page*)

Table 4 (*continued*).

BRBFNN BFO	Apple	Common rust, Cedar Apple rust, Late blight, Leaf curl, Leaf spot, and Early blight	–	–	Region growing algorithm (RGA)	V_{pc} and V_{pe}	I[st] set: 86.21 and 11.18 2nd set: 83.57 and 15.27	Chouhan et al. [22]
BP-ANN	Strawberry	Powdery mildew	BGR images converted into HIS	–	–	Precision	95.45	Mahmud et al. [23]
CNN	Cucumber	MYSV, ZYMV images of 2048 ×1536 and 2736 ×1824 pixels	Resize an image to 316 ×316-pixel, rotate images, Crop center areas and resize to 224 ×224-pixel using bi-linear interpolation	–	4-fold cross-validation	Accuracy	94.9	Kawasaki et al. [51]
	13 different plants	Powdery mildew, Downy mildew, Rust, Gray leaf spot, Wilt, Porosity, Taphrina deformans, Erwinia amylovora, and Gymnosporangium sabinae	Resized training dataset 256 × 256 pixels	–	YCbCr, HSI, and CIELB color models	Precision	96.3 after 100th epochs	Sladojevic et al. [244]
	Cucumber leaves	–	Resize to 316 X 316 pixels Augmentation: Image shifting, Image rotating, And image mirroring Trim to 224 X 224 pixels	–	–	Accuracy	*82.3*	Fujita et al. [245]
	Banana leaves	Black Sigatoka and black speckle	RGB to Grayscale color space, Resized dataset 60*60 pixels	–	CNN	Accuracy, Precision, Recall, f1-score,	85.94, 86.78, 85.94, 86.36	Amara et al. [246]
	25 different plants in a set of 58 distinct classes of plants and diseases	–	Resize images to 256 × 256 pixels	–	–	Accuracy	99.53	Ferentinos [56]
	Cannabis	Gray mold, Powdery mildew, yellow leaf spot, insects (Spider mites, Aphids), Nitrogen deficiency, Phosphorus deficiency, Potassium deficiency	–	–	–		90.79	Ferentinos et al. [247]

(*continued on next page*)

Table 4 (*continued*).

CNN model with high-level fusion	Rice	Leaf Blast(LB), Brown Spot(BS), Sheath Blight(SB), Bacterial Leaf Blight(BLB), Sheath Rot(SR), Leaf Smut(LS)	–	–	–		100	Vasantha et al. [248]
*	Citrus	Canker, Black spot, Huanglongbing, Healthy	Binary image and bounding box	–	–		94.37	Syed-Ab-Rahman et al. [249]
	Apple	,Marsonina Coronaria, Scab	Image rotation, flipping, scaling and introducing noise	–	–		99.2	Singh et al. [30]
Convolutional Encoder network	*2 Rabi crops:* Potato, Tomato, *1 Kharif crop:* Maize	Early blight. Late blight, Leaf mold rust, yellow leaf Curl virus	–	–	–		97.50 (2 × 2) 100 (3 × 3)	Khamparia et al. [250]
Updated CNN	Wheat (LWDCD2019)	Karnal bunt, Black Chaff, Crown and Root Rot, Fusarium Head Blight, Healthy Wheat, Leaf Rust, Powdery Mildew, Tan Spot, Wheat Loose Smut, Wheat Streak Mosaic	Resize to 224 ×224 pixels	–	–		97.88	Goyal et al. [251]
	Olive leaves	Peacock spot disease, Aculus olearius, healthy	Resize to 800 ×600 pixels, rotation, shifts, scaling, and horizontal flip or with techniques such as noise adding	–	–		95	Uğuz and Uysal [252]
	Citrus leaves	citrus black spot, citrus bacterial canker, and Huanglongbing or healthy class	Gray scale to binary	–	Anchor based CNN or two stage CNN		94.37	Syed-Ab-Rahman et al. [249]
Synthetic Minority Over-sampling Technique CNN	Cassava leaves	Whiteflies, Cassava brown streak virus disease, mottling, mosaic rust, twisted leaves. Cassava green mite, Cssava bacterial blight	–	–	–	Precision	96, 93, 93, 92	Sambasivam and Duncan [64]
Decision tree	Tomato leaves	–	Calculate 15 color features	Blob based segmentation	–	Precision, Re-call	0.88, 0.80	Yamamoto et al. [253]
DenseNets with 121 layers	14 plants of the Plant village dataset	–	–	–	–	Accuracy	99.75 for 30th epochs	Too-Edna et al. [254]

(*continued on next page*)

Table 4 (*continued*).

Nine-layer DCNN	39 different classes of plant leaves	–	Image flipping, Gamma correction, Noise injection, PCA, color augmentation, Rotation, and Scaling	–	–	96.46	Geetharamani and Pandian [255]
DENS-INCEP network model	Rice	Rice stuck burn, Leaf scald, Leaf smut, Whitetip, Bacterial leaf streak, Rice false smut, Rice blust, Rice stem rot, Rice sheath spot, Rice sheath rot, Grain spotting and Peck, Rice kernel smut, and Rice sheath blight	Resize, Image sharpening, Image edge filling, *Data augmentation*- color jittering, Random Rotation, Flipping, Translation, Cropping, and Scale transform	–	–	98.63	Chen et al. [256]
DLCNN	Tomato (Plant village)	bacterial Spot, late blight, sartorial Leaf Spot, tomato mosaic, yellow curved and healthy	Resize image 143 $\times$143 x3	–	–	96.43	Salih [257]
Delta Tributary network	Plant village	–	–	–	–	96	Gunasekaran and Gunavathi [258]
DenseNets201	Tomato (Plant village)	Bacterial spot, early blight, leaf mold, septoria leaf spot, target spot, two-spotted spider mite, late bright mold, mosaic virus, and yellow leaf curl virus, Healthy	Resize to 224 $\times$224 pixels and normalize images using mean, standard deviation, and z-score. *Data-Augmentation*- Rotation, Scaling, Translation	–	–	98.05	Chowdhury et al. [259]
DenseNet		tomato bacterial spot, tomato early blight, tomato leaf mold, tomato Septoria leaf spot, tomato spider mites, tomato target spot, tomato yellow leaf curl virus, and tomato mosaic virus.	Resize to 224 $\times$224 pixels	–	–	98.25	Rubini and Kavitha [260]

(*continued on next page*)

Table 4 (*continued*).

Extreme Gradient Boosting or XGBoost	Rice (UCI)	Brown spot, Leaf smut, Bacterial leaf blight	RGB TO HSV conversion	Binary thresholding	Mean of the red, green blue channel, mean of hue, saturation channel, the standard deviation of the red, green, and blue channel, normalized hue-saturation histogram, skewness, kurtosis, and standard deviation of the intensity values, GLCM		86.58	Azim et al. [261]
EfficientNet-B7	Tomato (Plant village)	Bacterial spot, early blight, leaf mold, septoria leaf spot, target spot, two-spotted spider mite, late bright mold, mosaic virus, yellow leaf curl virus and bacterial, viral, fungal, mold, and mite disease, Healthy	*Classification*- Resize to 224 ×224 pixels *Segmentation*- the pixels are also resized to 256 × 256 for the various variants of U-net models. *Normalize*- images using mean, standard deviation, and z-score. *Data Augmentation* -Rotation, Scaling, Translation	Modified U-net	–		99.95	Chowdhury et al. [259]
B4, B5 Models of EfficientNet	PlantVillage	–	–	–	–	Accuracy, Precision	99.97, 99.39, 99.91, 98.42	Ümit et al. [262]
Fuzzy Relevance Vector Machine (FRVM)	ICL leaf	–	Cellular automata filter, histogram equalization,	ROI segmentation	Haralick texture with Gabor, shaped based feature, color features *Feature Selection* Kernel-based PSO	Accuracy Precision Recall	99.87 99.5 99.9	VijayaLakshmi and Mohan [263]
IMPS-ELM	TPMD sensor-based dataset of tomato	Powdery mildew				AUC, CA	89.19 88.75	Bhatia et al. [44]
ELM	Tomato	Early_Bligh (EB) Late_Blight(LB), , Leaf_Mold , Target Spot, Healthy	Bilateral filter	Kaprus thresholding	EPO-MobileNet	Accuracy Precision Recall F-score Kappa	0.985 0.9892 0.987 0.985 0. 985.	Ashwinkumar et al. [264]

(*continued on next page*)

Table 4 (*continued*).

GoogLeNet	14 different crops	26 different kinds of diseases (PlantVillage dataset)	Resized images 256 × 256 pixels				99.35	Mohanty et al. [265]
Gabor Capsule Network	Tomato (Plant Village-Citrus dataset)	healthy leaves and Blackspot, Canker, Scab, Greening, and Melanose.	Resized to 48 ×48, 68 ×68, 224 ×224 pixels	–	–	Accuracy	98.13	Kwabena et al. [266]
Inception v3	Cassava leaves	Brown leaf spot (BLS), 96% for red mite damage (RMD), 95% for green mite damage (GMD), 98% for cassava brown streak disease (CBSD), and 96% for cassava mosaic disease (CMD).	–	–	–		CBSD-98 and GMD-95	Ramcharan et al. [267]
	Gingko	Healthy, mild, severe	Resized to 5184 × 3456 px to 1800 × 1200 pixels	–	–		93.2	Li et al. [268]
KNN	Oil palms	basal stem rot disease (Ganoderma)	–	–	–		97	Liaghat et al. [25]
	Maize leaves	5 different diseases	RGB to HSV	–	–		91	Zhang et al. [26]
	Groundnut	Early leaf spot, Late leaf spot, Rust, Bud necrosis, Alternia leaf spot [269]	Histogram Equalization, Gaussian Filter for removing noise, RGB to binary image	HSV segmentation with thresholding mask	Harris, HOG	Accuracy, Precision	97.67, 98.97	Devi et al. [29]
Fuzzy combined KNN	Tomato	Normal and sick	Convert RGB to HSV		Co-occurrence matrix		98.38	Jakjoud et al. [27]
LDA	Salad leaves (Spinach, rocket leaves)	Stemphylium and spinach crown mite	–	–	Feature selection-PCA, Multi-statistics test (Kullback–Leibler distance and ROC)	Accuracy	84	Dutta et al. [270]
LeafNet	185 tree species	–	Data augmentation	–	–		86.3	Barré et al. [271]
LeNet	Tomato PlantVillage	Yellow Leaf Curl Virus, Target Spot, Spider mites, Septoria leaf spot, Mosaic virus, Leaf Mold, Late blight, Healthy, Early blight, Bacterial spot	Resized into 64 × 64 pixels	–	–		96.27	Kumar and Vani [272]
Learning Vector Quantization (LVQ)	Soybean	Blight, Frogeye leaf spot and Septoria brown spot, Healthy leaves	–	–	6 color features, 2 texture features		93	Udupi [273]

(*continued on next page*)

Table 4 (*continued*).

MLP	Avocado	Laurel wilt, Spectral data from healthy, Phytophthora root rot	–	–	–		100	De Castro et al. [274]
PLSR	Winter Wheat leaf	Yellow rust	–	–	–	R^2, RMSE	0854, 0.104	Yuan et al. [275]
NNE	Mango	Dag, Red rust, Sooty mold, Golmachi	RGB to L*a*b* color space	K-means	GLCM	Accuracy	80	Mia et al. [35]
RBPNN	Leaves	–	–	–			93.82	Kulkarni et al. [276]
Random Forest (RF)	24 different medicinal plants	–	Median blur filter with a window size of 25, Otsu's threshold operation (RGB to the binary image), Erosion and Dilation	–	Bounding box and contour, convex hull, vertical distance map, horizontal distance map, and radial map. 10-fold cross-validation		90.1	Begue et al. [277]
	Jackfruit	Rhizopus Rot, Leaf spot, pink disease, pest, and disease	RGB to L*a*b* color space	K-means clustering	Statistical feature and GLCM		89.52	Habib et al. [278]
	PlantVillage	–	Average, Linear, Median, and Adaptive filters	Otsu technique	GLCM	Accuracy, F-score, Recall, Precision	73.38,71.98, 72.90,72.90	Ganatra and Patel [73,74]
Extremely Randomized tree	Banana leaves	banana bacterial wilt (BBW) and banana black Sigatoka (BBS			Color Histogram from RGB to HSV, RGB to L*a*b*	AUC	BBW 0.96 BBS 0.91 Healthy 0.99	Owomugisha et al. [279]
RBF	Sugar belle leaves	Citrus canker	–	–	–	Accuracy	96	Abdulridha et al. [280]
faster R-CNN	Sugar beet	Low, Severe, Healthy	–	–	–		98.45	Ozguven and Adem [281]
ResNet-50	Wheat	Rust, Tan spot, Septoria	Resize image, Leaf mask crop, Super pixel-based tile extraction	SLIC	–	Balanced Accuracy	96	Picon et al. (2019)
	Strawberry	Crown leaf, blight leaf, fruit leaf blight, Gray mold, powdery mildew	–	–	–		*Original data:* 98.06 *Feature data:* 99.06	Xiao et al. [282]
ResNet-101	Tomato (Plant village)	Early blight (i.e., mild, moderate, and severe early blight) and Healthy	*Data Augmentation-* Rotation, Scaling, Translation	–	–	Accuracy	94.6	Prabhakar et al. [283]

(*continued on next page*)

Table 4 (*continued*).

	Plant village	Apple scab, Apple black rot, Cercospora leaf spot, Northern leaf blight, Maize common rust	–	–	–	99.73	Ganatra and Patel [73,74]
SVM	Sugar beet	Cercospora Leaf spot, Leaf rust, and Powdery mildew	–	–	with RBF kernel	97	Rumpf et al. [32]
	Wheat	Leaf rust	–	–	4th order polynomial	93	Römer et al. [284]
	Oil Palm Leaves	nutrition diseases like nitrogen, potassium, and magnesium	Resized to 504 × 755 then apply a median filter	–	Color, Histogram-based texture features (based on RGB color), and Gray level co-occurrence matrix.	95	Asraf et al. [285]
	Sunflower	Black spot, bacterial leaf spot, downy mildew	Vector median filter	Optional threshold segmentation method based on R and H components	Color feature HSI, texture feature GLCM	Initial Stage-60, Mid Stage-92.5, Late Stage-75	Xu et al. [286]
	Tomato leaves	–	–		*Feature reduction* PCA, *Color feature* GLCM	92	Semary et al. [287]
	Sugar beet	Cercospora leaf spot,	–	–	Entropy X Density	Training-98.48, Testing-97.44	Zhou et al. [288]
	Tomato leaves	tomato late blight, Septoria spot, bacterial spot, bacterial canker, tomato leaf curl and healthy tomato plant leaf [272]	–	–	max(R), Max(G), Max(B). Two feature vectors computed from each R, G, B, i.e., mean and standard deviation. Then computed mean(R), mean(G), mean (B) and std2(R), std2 (G) and std2 (B)	97.3	Sabrol and Satish [289]
	Leaves	Leaf rust	SF-CES	K-Means	GLCM	93.79	Tripathi and Maktedar [290]
	Vegetable crop	Mosaic, Alternia Alternata, Anthracnose, Cercospora Leaf Spot, Bacterial Blight	CIELAB	K-Means, Otsu	Co-occurrence matrix	92.4	Pooja et al. [291]
	Tea	Brown blight, Algal	Normalized RGB to Grayscale image	–	–	93	Hossain et al. [292]

(*continued on next page*)

Table 4 (*continued*).

Sugarcane	RGB to Grayscale image	Borer disease	Threshold segmentation with area selection, Filling corrosion operations, Adaptive threshold technique	with RBF kernel function and Polynomial kernel function		Polynomial-100 RBF-95.83 (Testing dataset)	Huang et al. [293]
Chilli, Grape, Rice, Soybean, Wheat, Rose, Cotton, Apple, Mango	Bacterial blight and Cercospora leaf spot, Powdery mildew, and Rust.	Resized RGB to HSV images, Median filters to remove noise and smooth image.	K-means clustering	GLCM and LBP texture feature extraction methods (with cubic kernel and 10-fold cross-validation)		98.2, error rate 0.8	Oo and Htun [294]
Acer campestre, Acer palmatum, Aesculus-pavi, Catalpa speciosa and Paulownia tomentosa leaves.	–	Resized to 256 × 256 pixels	K-Means cluster, Convert binary images into LAB	GLCM		96	Shobana et al. [295]
Cotton leaf	–	–	K-Means, inconsistent cluster (ICA)	*Feature Descriptors* SURF, SIFT, FREAK	Precision	94.44	Prashar et al. [296]
Pear	Alternaria [297] alternata	Resize spectral range of 400–1000 nm and 1st order derivative, multiplicative signal correction (MSC), and mean centering to remove ambient noise in raw spectral data	RGB image, Mask image, Maximum likelihood, SAM image	PCA	Accuracy	97.5	Pan et al. [298]
Rice	Blast, Red blight, Stripe blight, Sheath blight.	Resized to 800*600 pixels	CNN	CNN		96.8	Jiang et al. [299]
	Bacterial Leaf Blight, Rice Blast, Sheath Blight, and Healthy Leave	RGB to: Normalized-RGB, YCbCr, HSV, HSI, CIE XYZ, CIE Lab, CIE LCH, CIE Luv, Hunter-Lab, SCT, opponent, CMY, and CMYK.	–	Color feature extraction, statistical feature extraction		94.65	Shrivastava and Pradhan [300]

(*continued on next page*)

Table 4 (*continued*).

SVM, adaptive OCM (template)	Sugar beet	Healthy, Cercospora leaf spots	–	Index of G-R	CIE feature extraction	96.52, 99.47	Rong et al. [301]
Multiclass SVM	Mango leaves	Anthracnose, Red rust, Sooty mold, Scab	RGB to HIS	K-means	GLCM	96	Srunitha and Bharathi [302]
	CASC-IFW datasets	Apple scab, Apple rot, Banana Sigatoka, Banana cordial leaf spot, Banana diamond leaf spot, and Deightoniella leaf and Fruit spot	Top hat filter, Adjust intensities, Max/Min global values, Contrast range, Low/ High threshold, and Final threshold	–	VGG16, Café-AlexNet, Feature selection-Genetic algorithm	98.60	Khan et al. [303]
	Flavia dataset	–	RGB to Grayscale using threshold segmentation, Then Grayscale to binary images, reduce noise by using average filtering and edge detection using a Laplacian filter	–	Shape + Vein features	97	Goyal et al. [304]
TSVM	Rice	–	Resized to 256*256 pixels And median filter	K-means	Contrast, Energy, Entropy Homogeneity, RMS, Variance, Smoothness, Kurtosis, Skewness, Correlation	95	Chawal and Sanjeev [47]
Fuzzy TSVM	First leaf dataset, Second leaf dataset	–	*First leaf dataset* Binary image-shape feature Grayscale image-Texture feature *Second leaf dataset* Binary image for feature extraction	*Second leaf dataset* Global thresholding on gray scale images	*First leaf dataset* shape attributes features (Eccentricity, Aspect Ratio, Elongation, Solidity, Stochastic Convexity, Isoperimetric Factor, Maximal Indentation Depth and Lobedness) and 6 texture features (Average Intensity, Average Contrast, Smoothness, The third moment, Uniformity and Entropy) *Second leaf dataset* Shape, Texture, margin features	*First leaf dataset* Linear kernel-96.89 Polynomial kernel-98.12 Gaussian kernel-97.61 *Second leaf dataset* Linear kernel-99.12 Polynomial kernel-99.44 Gaussian kernel-99.54	Laxmi and Gupta [42]

(*continued on next page*)

Table 4 (*continued*).

Spectral vegetation indices using hyperspectral imaging data	Sugar beet	Healthy sugar beet leaves and leaves infected with Cercosporaleaf spot, Sugar beet rust, and Powdery mildew	–	–	RELIEF-F		89, 92, 87, 85	Mahlein et al. [305]
SCANet	Pinewood	Nematode disease and other 59 diseases	–	–	–	Accuracy, Mean precision, Mean recall	79.33, 86.0, 91.0	Qin et al. [306]
VGG16	Tea leaves	Red leaf spot, Leaf blight, red scab	C-DCGAN	SVM	Color and texture feature extractors		90	Hu et al. [72]
	Tomato (Plant village)	–	—-	–	SVM, KNN	Accuracy	97.82	Mohameth et al. [307]
	Maize	Common Rust disease (Early-stage, Middle stage, Late Stage, and Healthy stage)	–	Otsu's threshold-segmentation	Fuzzy decision rules		Validation 95.63 *Testing* 89	Sibiya and Sumb-wanyambe [308]
ANN and Decision tree (CART)	Citrus Fruits	Penicillium genus	–	–	Feature selection- MRMR		98	Gómez-Sanchis et al. [309]
AlexNet, ResNet,	Citrus plants	Phyllocnistis citrella, lack of element, scale insects	Size of Alexnet is (227 × 227x3) and (224 × 224x3) for ResNet model. *Augmentation:* Random reflection in the left–right direction. The width of horizontal translation is applied to the input image; the pixel scale of the translation distance [30, -30] is determined.	–	–		*With data augmenta-tion* 97.92 95.83 *Without data aug-mentation* 95.83, 93.75	Luaibi and Salman [310]

(*continued on next page*)

Table 4 (*continued*).

DCNN with NAG	Apple	Black spot, Mosaic, Rust, and Alternia leaf spot	Resized RGB to 256 × 256 pixels, Direction disturbance, Light disturbance, and PCA jittering	–	–	97.62	Liu et al. [311]
MLP, SVM	PlantVillage bell pepper dataset	Bacterial spot, Healthy	–	–	Color features, mixture model-based county expansion, Fisher vectors Feature selection-PCA	94.35	Kurmi et al. [312]
RBF, SOM	Ethiopian coffee	Coffee leaf rust, Coffeeberry disease, and Coffee wilt disease [313]	RGB to Grayscale images, Resized into 360 ×360 pixels, Reduce low-frequency background noise, remove reflection, Masking portion of an image, and use a median filter	K-means clustering	GLCM, Color space	90.07	Mengistu et al. [314]
Hybrid deep learning with SVM	leaf	–	24-bit date RGB image changes into 8-bit data gray image.	–	–	93	Liu et al. [315]
SVM, KNN	Strawberry	Powdery Mildew	Convert BRG to G ratio and HIS		Perform texture feature extraction from CCM	91.86, 83.20	Mahmud et al. [316]
S-CNN, F-CNN	Tomato (Plant Village)	Bacterial Spot, Early Blight (B), Late Blight (LB), Leaf Mold, Septoria Leaf Spot, Spider Mite, Target Spot, Tomato Mosaic Virus, Yellow Leaf Curl Virus, Healthy	–	–	–	98.60	Sharma et al. [317]

(*continued on next page*)

Table 4 (*continued*).

Faster RCNN, DR-IACNN	Grape	Black rot, Leaf blight, Black measles, and mites	Data augmentation, Data annotation	–	Inception-v1 module, Inception-ResNet-v2 module and SE-blocks	Precision	81.1	Xie et al. [318]
Random forest, SVM, KNN	Alfalfa leaf	Common leaf rust, Cercospora leaf spot, Leptosphaerulina leaf spot	RGB to HSV color space and RGB to L*a*b* color space	*Clustering Algorithm* (K-means clustering, Fuzzy C-means clustering, K-median Clustering) *Supervised Learning Algorithms* (Logistic regression, Naive Bayes, Regression tree, and LDA)	*Feature selection methods* (ReliefF, 1R) *Correlation-based feature selection*	Accuracy	Training - 97.64 Testing - 97.74	Qin et al. [319]
Faster R-CNN, R-FCN, and SSD	Tomato and Pest	Gray Mold, Canker, Leaf mold, Powdery mildew, Pest- (Plague, Whitefly, Leaf miner)	*Annotation-* Annotates images with a bounding box, *Class Augmentation-* Geometrical transformations (Resizing, crop, rotation, horizontal flipping), Intensity transformations (contrast and brightness enhancement, color, noise).	–	AlexNet, ZFNet, VGG16, GoogLeNet, ResNet-50, ResNet-101, ResNetXt-101	Average Precision	R-FCN with ResNet-50 to 85.98	Fuentes et al. [320]
VGG-FCN-VD16 and VGG-FCN-S	Wheat	Powdery mildew, Smut, Black chaff, Stripe rust, Leaf blotch, Leaf rust	Resized RGB images 832 ×832 x 3	–	Contour extraction		97.95, 95.12	Lu et al. [321]
GoogLeNet-based learning rate-0.001 Cifar-base learning rate-0.00002 iteration-100	Maize	Brown spots, Curvularia leaf spot, dwarf mosaic, Gray leaf spot, northern leaf blight, round spot, rust, and southern leaf blight	Resized to 32 ×32 bits per inch, RGB to grayscale images and Rotate images in 90, 180, and 270 degrees.	–	–	Accuracy	GoogLeNet-98.9 Cifar10-98.8	Zhang et al. [322]
GoogLeNet inception structure with rainbow concatenation or INAR-SSD	Apple	Alternia Leaf spot, Mosaic, Rust, Gray spot, Brown spot	Data annotation, Data augmentation	–	–		97.14	Jiang et al. [323]
Inception-v3, Resnet-50, VGG-19 and Xception	Soybean	Asian rust, target spot, mildew, powdery mildew, Healthy	–	SLIC	–		99.04	Tetila et al. [324]
Faster-R-CNN Inception v2	Grape (Plant village)	Infected leaves and healthy leaves	–	–	–		95.57	Ghoury et al. [325]

(*continued on next page*)

Table 4 (*continued*).

CNN based model (3 convolutional layers, 3 max-pooling layers followed by 2 fully connected layers)	Tomato	Target spot, Mosaic virus, Bacterial spot, Late blight, Leaf mold, Yellow Leaf curl Virus, *Spider mites:* Two-spotted spider mite, Early blight, and Septoria leaf spot	*Augmentation:* Flipping, Rotating, Cropping, and Resizing images to 256 × 256 pixel	–	–		91.2	Agarwal et al. [58]
(ResNet18, ResNet34, and ResNet50) to make two baseline architectures a triplet network and a deep adversarial metric learning approach	PlantVillage	–	–	–	–		81	Afifi et al. [326]
MobileNetV3 small and MobileNetV3 large	PlantVillage	Bacterial Spot, Early Blight, Late Blight, Yellow leaf Curl Virus, Target Spot, Septoria Leaf Spot, Two-spotted spider mites, Mosaic Virus, Leaf Mold	Fixed-size of 256 × 256 pixels.	–	–		98.99, 99.81	Tarek et al. [327]
Logistic, MLP, SVM, KSTAR, AdaBoostBagging, PART, J48, Random Forest with 10-fold cross-validation	Red palm weevil	–	–	–	*Feature Selection:* Pearson's correlation coefficient	Accuracy, Precision, Recall, F-measure	93, 87, 100, 93	Kurdi et al. [328]
VirLeafNet-1, VirLeafNet-2, VirLeafNet-3 (CNN)	Vinga mango	Yellow mosaic disease (Severe Infected, Mild Infected, Healthy)	–	–	–	Accuracy	91.2343, 96.429, 97.403	Joshi et al. [329]
Deep layer-ResNet50, DenseNet121, Machine Learning Method-LR	Peanut	Healthy leaves, Rust disease, Leaf-spot, Scorch disease [330]	Data-augmentation methods-image flipping, rotation, and scaling	–	–	Accuracy, Recall, F1-score	97.59 93.08 93.80	Qi et al. [75]
depth-wise separable convolutional PLD (S-modified MobileNet), (S-reduced MobileNet), and (S-extended MobileNet)	leaf	–	–	Modified adaptive centroid-based segmentation	–	Accuracy, F1-score	99.55, 97.07	Hossain et al. [331]

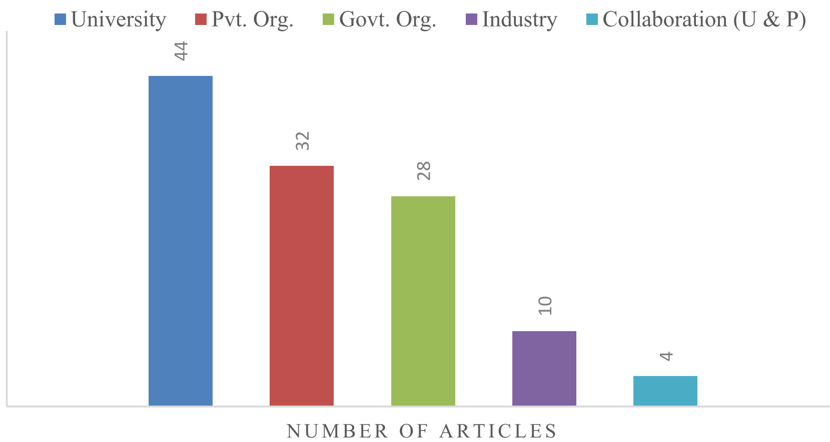


Fig. 8. Number of articles supported by several organizations.

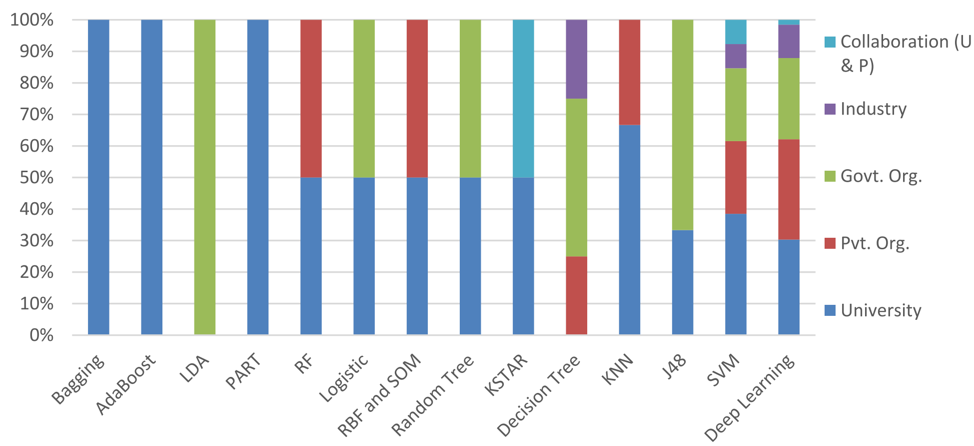


Fig. 9. Currently selected ML and DL-based models by several organizations.

area, Sa = number of lesions are obtained by the region pixel using jump detection method, L_P = physiological length, W_P = physiological width, AB = area of bounding box, A = Leaf area is total number of pixels in binary image equal to 1 after filtering and it is denoted as A, P_K = leaf perimeter (total number of pixels on the boundary of the leaf image), σ = standard deviation; $a*$ = green (in negative direction) to red (in positive direction) and $b*$ = indicates blue (in the negative direction) to yellow (in the positive direction) conversion. c, d = are certain intensity levels N = the total number of intensity levels, $p(c, d)$ = the (c, d)th entry in a normalized CCM.

Notations. TP = true positive; FP = false positive; TN = true negative; FN = false-negative; TPR = true positive rate; TNR = true negative rate; $\boldsymbol{M}$ = a number of positive samples, N_i =number of negative samples, $\boldsymbol{N}$ = number of samples, N_K =number of samples in class K, $\boldsymbol{Rc}$ = the recognition rate of each class, $\boldsymbol{No}$ = number of successful attempts, $\boldsymbol{E}$ = external failure, $\boldsymbol{T}$ = the total number of attempts, mP = mean precision, mR = mean recall, x_i = the value of x variable in a sample, y_i = the value of y variable in a sample, $\bar{x}$ = mean of the value of x variable, $\bar{y} = \bar{x}$ = mean of the value of y variable, RSS = a sum of the square of residuals, TSS = Total sum of the square, K = number of clusters, NP = the total number of an image pixel, $u_1, u_2, \ldots, u^h$ =The hidden layer is a radial center.

3. Methodology

This section consists of three subsections such as methodology, data collection and different stages of leaf disease classification. Methodology diagrammatically shows the steps of leaf disease detection for machine learning and deep learning models. Data collection is nothing but several datasets that have been adopted by several researchers in previous work. In different stages of the leaf disease classification subsection, several algorithms of every stage have been explained shortly.

To identify infected leaves using ML and DL, the following steps are shown in Figs. 12 and 13. There are a few basic steps that are essential for obtaining an accurate diagnosis of leaf disease. It is a systematic methodology that is utilized in the leaf disease classification process by using ML and DL. The following are the important stages of leaf disease detection: (1) Image acquisition, (2) Image pre-processing, (3) Segmentation, (4) Feature selection and extraction, and 5) Classification.

3.1. Dataset collection

Many datasets are required to train an ML or DL model for the classification and diagnosis of leaf illness. In pre-processing, the original dataset is augmented to create an enlarged and scaled dataset. Here, we discuss some of the available datasets like PlantVillage, LeafSnap, Foliage, Flavia, Apple leaf disease, Wheat disease [344], Rice disease, and the miscellaneous dataset as mentioned in Table 5 with its repositories.

Table 5
List of Features extraction, selection, Data annotations, and Segmentation metrics used in selected research papers.

Indicator	Formula	Indicator	Formula
Marginal probability index $P_x(i)$	$\sum_{j=0}^{N_g-1} P(i,j)$	Ratio (R)	$\frac{I_{red}}{I_{green}}$
Contrast (c)	$\sum_{i=1}^{m}\sum_{j=1}^{m}(i-j)^2 P_{ij}$	Variance (S^2)	$\frac{\sum(X-\overline{X})^2}{N-1}$
Correlation (co)	$\sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j}$	Kurtosis (k)	$\frac{\sum_{i=1}^{n}(Y_i-\overline{Y})^4}{n-1}s^4$
Energy (E)	$\sum_{i=1}^{m}\sum_{j=1}^{m}P_{ij}^2$	Skewness (Sk)	$\frac{\sum(y_i-y)^3}{(n-1)^3}$
Moment (M)	$\sum_{i,j}(i-j)^3 p(i,j)$	Color ratio (r)	$\frac{R}{R+G+B}$
Homogeneity (H)	$\sum_{i=1}^{m}\sum_{j=1}^{m}\frac{P_{ij}}{1+\lvert i-j\rvert}$	Color ratio (g)	$\frac{G}{R+G+B}$
Entropy (En)	$-P_+\log 2\,(P_+) + (-P_-)\log 2\,(P_-)$	Color ratio (b)	$\frac{B}{R+G+B}$
CCM (Co-occurrence methodology)$P\,(i,j)$	$\frac{P(i,j,1,0)}{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}P\,(i,j,1,0)}$	Circularity (C)	$\frac{4\Pi S}{L^2}$
Complexity (Cp)	$\frac{L^2}{S}$	Chroma (C^*ab)	$\sqrt{(a^*+b^*)}$
First Moment (μ_1)	$\frac{1}{L}\sum_{i=0}^{L-1}f_{ij}p\,(f_i)$	Hue Angle (HA)	$\tan^{-1}\left(\frac{b^*}{a^*}\right)$
Second Moment (μ_2)	$\left[\frac{1}{L}\sum_{i=0}^{L-1}(f_i-\mu_1)^2\,p(f_1)\right]^{\frac{1}{2}}$	Solidity (So)	$\left(\frac{area}{Hullarea}\right)$
Third Moment (μ_3)	$\left[\frac{1}{L}\sum_{i=0}^{L-1}(f_i-\mu_1)^3\,p\,(f_1)\right]^{\frac{1}{3}}$	Rectangularity (Re)	$\left(\frac{width\times length}{area}\right)$
Intensity (I)	$\left(\frac{R+G+B}{3}\right)$	Convexity (Co)	$\left(\frac{Hullperimeter}{perimeter}\right)$
Saturation (S)	$1-\left(\frac{3\min(R,G,B)}{(R+G+B)}\right)$	Angular Second Moment (ASM)	$\sum_{i}\sum_{j}P_d^2(i,j)$
Hue (H)	$1-\left(\frac{(R-G)+(R-B)}{\sqrt{(R-G)^2+(R-G)(G-B)}}\right)$	Inverse Difference Metrics (IDM)	$\sum_{i=0}\sum_{j=0}\frac{1}{1+(i-j)^2}p(i,j)$
GLCM(G)	$\sum_{i,j=0}^{J-1} iP_{ij}$	Smoothness (R)	$1-\frac{1}{1+\sigma^2}$
Standard Deviation (σ)	$\sqrt{\frac{\sum(x_i-\mu)^2}{n}}$	White area ratio (W)	$\frac{AB-area}{AB}$
Lobidity (L)	$\frac{Perimeter}{(width+length)}$	Hull ratio (HR)	$\frac{Hullarea}{Hullperimeter}$
Hydraulic radius (Hr)	$\frac{area}{perimeter}$	Aspect ratio (Ar)	$\frac{L_P}{W_P}$
Lesion Area (LA)	$\sum_{x=1}^{n}\sum_{y=1}^{m}f\,(x,y)$	The ratio of Lesion Area (RL)	$\frac{LA}{Sa}$
Mean $(\overline{X})$	$\frac{\sum_{i=1}^{n}X_i}{n}$	Product of moment (Pm)	$\sum_{c=0}^{N-1}\sum_{d=0}^{N-1}p\,(c,d)\,(c-X)\,(d-X)$

3.1.1. Plantvillage dataset

The plantVillage dataset [340] is probably the most usable dataset for the research of leaf disease detection. The dataset consists of 50,000 images, with 26 diseases for 24 crop plants. These training samples have been further processed with a 10-fold cross-validation technique through research work to obtain an equal number of training and testing datasets, some studies have considered a small number of samples instead of ample datasets for their purpose and rotated these images into different degrees and then divided into different ratios to obtain different training, validation, and test ratios.

3.1.2. Leafsnap, foliage, and flavia datasets

Datasets for LeafSnap [336], Foliage [333], and Flavia [332] have been considered in many studies [271]. High-quality RGB (256 × 256 pixels) images of 185 tree species in the LeafSnap dataset are lab images and field images. After an increase of 23 147 augmented lab images and 7719 augmented field images, many datasets (270161 images) have been applied to train the model. In [304], 1907 images of 32 different common plants have been collected from the Flavia dataset.

3.1.3. Apple leaf disease detection (ALDD)

In this experiment, ALDD dataset images have been collected under different weather conditions [323]. A total of 2029 images are composed of five several diseases of the apple plant.

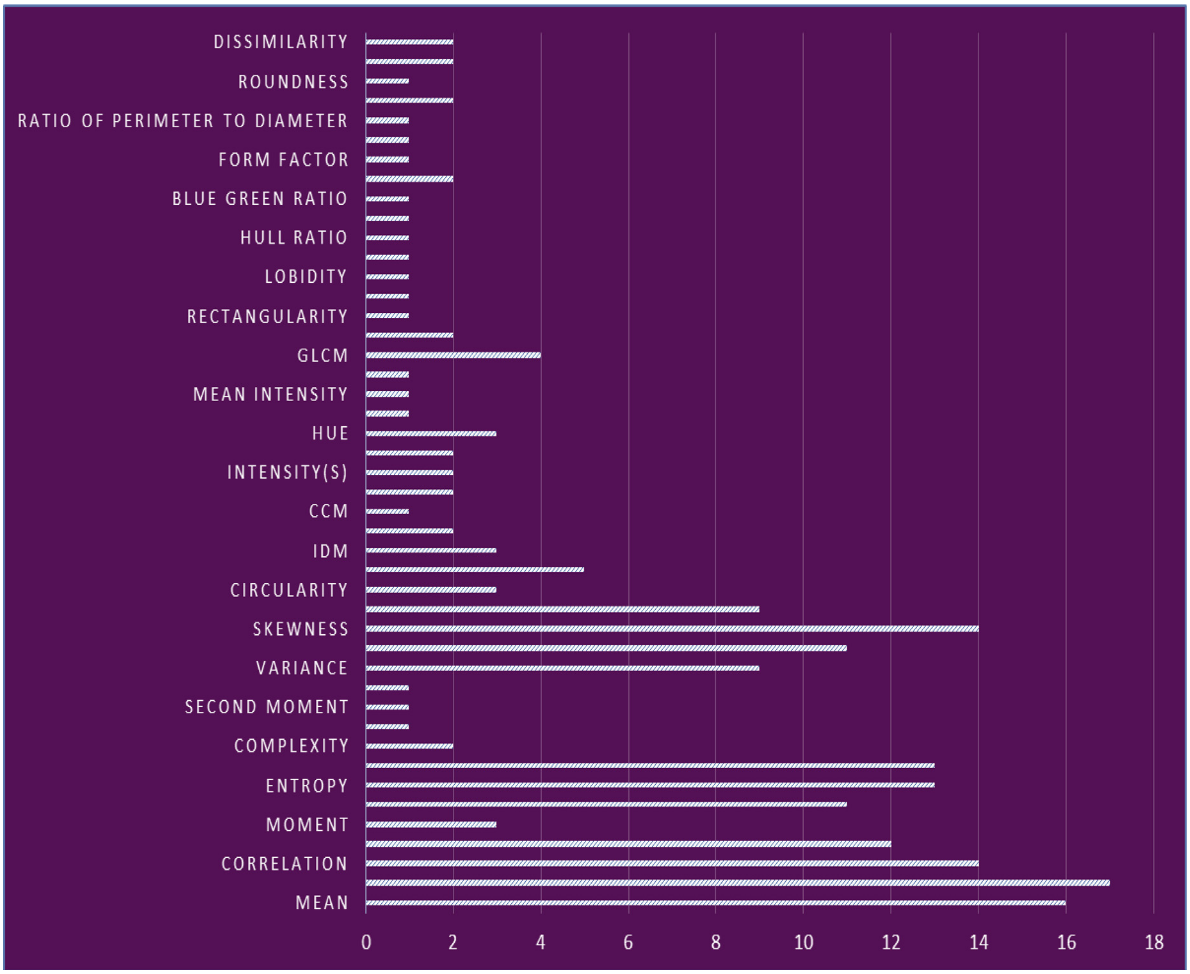


Fig. 10. Clustered Graph for Features extraction, Selection, Data annotations, and Segmentation metrics used in research papers on applicable models on plant/leaf disease from June 2010 to December 2022.

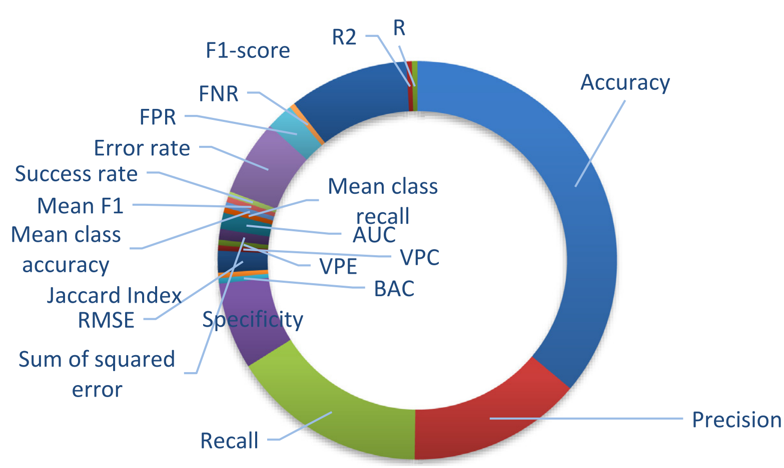


Fig. 11. Doughnut Graph for Performance parameters used in selected research papers on applicable models (such as SVM, RF, CNN, ANN, DT, ResNet, MLP, BPNN, VGG16, LR, and RBF) on leaf disease detection from June 2010 to December 2022.

The presence of the same images in this dataset and complex backgrounds in those images may hamper this experiment so the images have been annotated. After performing an annotation technique, 26,377 images are used as inputs to this proposed model.

3.1.4. Wheat disease database (WDD) 2017

The WDD2017 dataset consists of in-field wheat crop images (9230) which are divided into 5-fold and 4-fold cross-validation techniques and these images are used as a training set, 1-fold cross-validated images are used as a test set. In this [321] study, 350 images of powdery mildew, 1455 images of smut, 585 images

Table 6
List of performance parameters used in selected research papers.

Indicator	Formula	Indicator	Formula
F_1-score (F_1)	$\left(\frac{TP}{TP+\frac{1}{2}(FP+FN)}\right)$	RMS (Root Mean Square)(Rm)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
False Positive Rate (FPR)	$\left(\frac{FP}{FP+TN} \times 100\right)\%$	Success rate (Sr)	$\frac{No+E}{T} \times 100$
False Negative Rate (FNR)	$\left(\frac{FN}{TP+FN} \times 100\right)\%$	Mean class Recall (MR)	$\frac{\mathrm{Re}\times N_k}{N}$
Balanced Accuracy (BAC)	$\left(\frac{Se+Sp}{2}\right)$	Mean class accuracy ($mcAcc$)	$\frac{Rc\times N\ \ k}{N}$
Error Rate (Er)	$\left(\frac{FP+FN}{TP+TN+FP+FN} \times 100\right)\%$	Mean F1(mF)	$\frac{mP\times mR}{mP+mR}$
Precision (P)	$\left(\frac{TP}{TP+FP} \times 100\right)\%$	AUC(A)	$\frac{\sum_{i\in M} rank_i - \frac{M(1-M)}{2}}{M\times N_i}$
Accuracy (Acc)	$\left(\frac{TP+TN}{TP+TN+FN+FP} \times 100\right)\%$	SSE (Sum of Squared Error) (s)	$\sum_{i=1}^{n}\left(\overline{X}-X_i\right)^2$
Specificity (Sp)	$\left(\frac{TN}{FP+TN} \times 100\right)\%$	Correlation coefficient (Se)	$\frac{(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{(x_i-\overline{x})^2(y_i-\overline{y})^2}}$
Sensitivity (Se)	$\left(\frac{TP}{TP+FN} \times 100\right)\%$	Coefficient of determination (R^2)	$\frac{RSS}{TSS}$
Validation evaluation partition coefficient (V_{pc})	$\sum_{k=1}^{K}\sum_{i=1}^{NP}\frac{u_{ik}^2}{NP}$	Validation evaluation partition entropy (V_{pe})	$-\sum_{k=1}^{K}\sum_{i=1}^{NP}\frac{u_{ik}\log(u_{ik})}{NP}$
Jaccard Index (Ji)	$\left(\frac{TP}{TP+FN+FP}\right)$		

Table 7
Description of the popular leaf disease datasets.

Plant leaf datasets	Number of images	Number of crops	Repositories
Foliage [332]	–	–	http://www.leafnet.pbarre.de/
Flavia [333]	–	33	http://flavia.sourceforge.net/
Plant (object) detection dataset [334]	–	–	https://github.com/pratikkayal/PlantDoc-Dataset/
Apple leaf [335]	2029	1	https://www.quantitative-plant.org/dataset/apple-leaf-dataset/
LeafSnap [336]	30866	185	http://leafsnap.com/dataset/
Rice leaf disease [337]	120	1	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases/
Coffee leaf dataset [313]	1747	1	https://github.com/esgario/lara2018/
Rice disease dataset [338]	552	1	https://github.com/aldrin233/RiceDiseases-DataSet.git/
Plant disease dataset [339]	1710	12	https://data.mendeley.com/datasets/hb74ynkjcn/4/
PlantVillage [339,340])	50000	24	https://github.com/salathegroup/plantvillage_deeplearning_paper_dataset/ https://data.mendeley.com/datasets/tywbtsjrjv/
Plant disease dataset [341]	1569	20	https://www.digipathos-rep.cnptia.embrapa.br/
New Plant Diseases Dataset [342]	87,000	38	https://www.kaggle.com/datasets/
Flowers Recognition [342]	4242	4	https://www.kaggle.com/datasets/
Plant Seedings Dataset [343]	5539	12	https://datasets.bifrost.ai/
Weed Detection in Soybean Crops [342]	15536	4	https://www.kaggle.com/datasets/

of black chaff, 1755 images of stripe rust, 2455 images of leaf blotch, 1110 images of leaf rust have been used. Out of the six diseases, only one type of disease is annotated.

3.1.5. Miscellaneous dataset

Some researchers have considered online images and other captured images using cameras or smartphone devices for their research purposes. Online images have been captured in the greenhouse under natural sunlight with the help of a CCD camera and for classification purposes, total images are extracted based on color, shape, and texture. For this experiment, 8911 photos were taken [302], including 2274 images of healthy rice, 1634 photographs of rice blast, 1765 images of rice bacterial spot, 1678 images of rice streak leaf spot, and 1560 images of rice sheath blight. The images of 24 plants named tulsi, strawberry guava, pomegranate, peppermint, avocado, antiderma, ayapana, balloon, bitter gourd, parsley, bigaignon rouge, Bois carotte, Bois Cerf, and boisderat have been captured using smartphones to recognize different kinds of fruit and vegetables [277]. Image datasets are taken from agricultural universities containing 5 classes and each class consists of 61 images in anthracnose, 50 in red rust, 55 images in sooty mold, 75 in scab, and 45 images of healthy mango leaves [345]. Habib et al. [278] captured pictures of four different jackfruit diseases from a professional farmer's home in

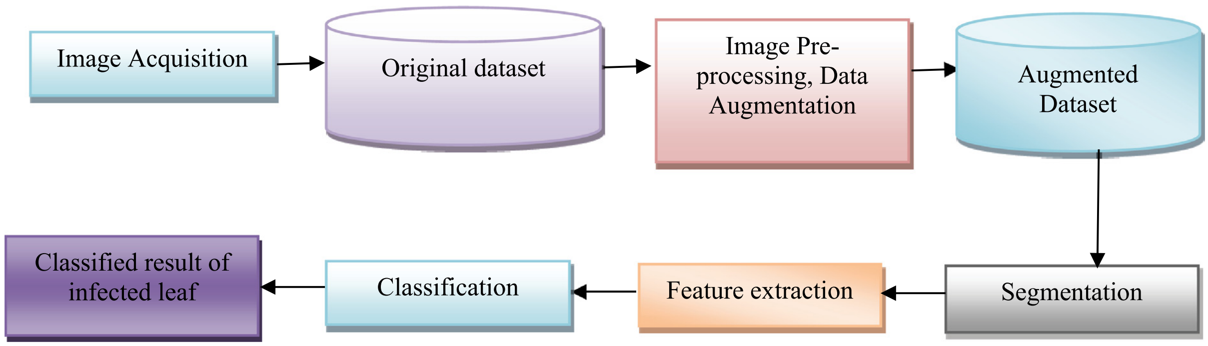


Fig. 12. Steps of leaf disease detection using machine learning.

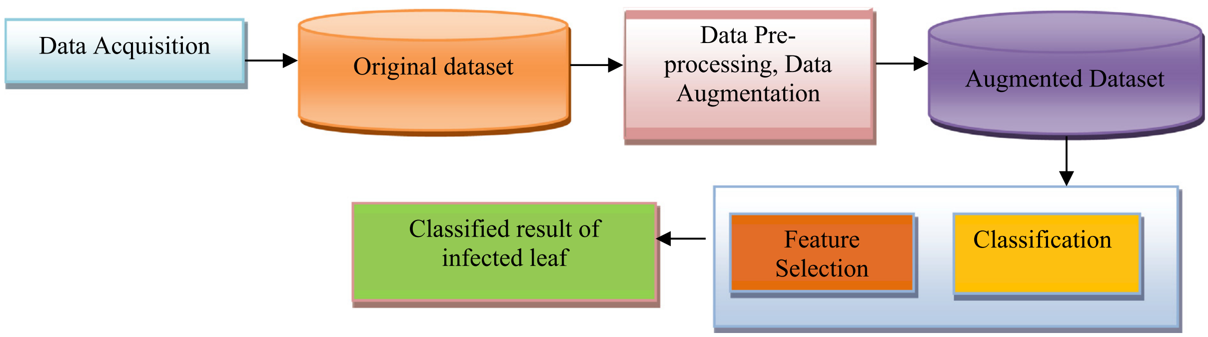


Fig. 13. Steps of leaf disease detection using deep learning.

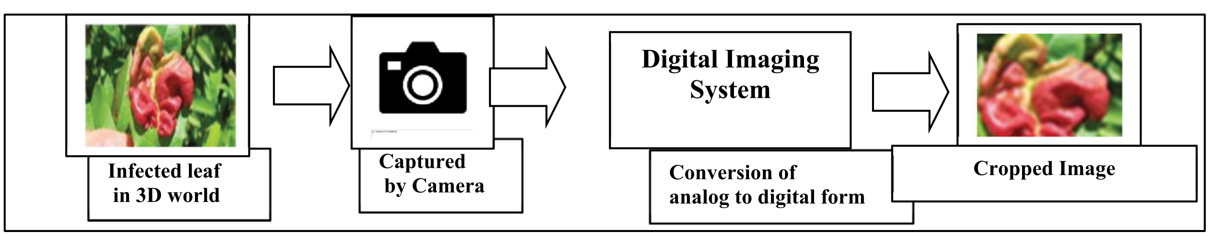


Fig. 14. Steps of Image Acquisition.

Bangladesh using a smartphone. Many images have been taken from the Bangladesh Tea Research Institute located in Sri Mongol Bangladesh [292]. Table 7 describes the popular leaf disease datasets along with their repositories.

3.2. Different stages of leaf disease classification

3.2.1. Image acquisition

A digital camera usually captures images in RGB mode or Gray mode so that different image datasets can be applied as input images for the next steps of this purpose. To capture an image of an infected leaf by a digital camera or android mobile these steps are usually followed as this object is in 3D form and it consists of continuous values. It cannot be stored in computer memory as it does not support analog or infinite values. So, Analog to digital conversion of this image is needed which is performed at the time of capturing an image by any of these two types of equipment, and then we can operate (image size adjustment, image quality enhancement, etc.) with this image [7]. A conventional method of image acquisition can be represented as follows (see Fig. 14):

The fluorescence technique for collecting photos of crops is shown in Fig. 15. [334]. This technology captures photos of living infectious organisms in leaves using fluorescence imaging and UV radiation. The idea behind this imaging is that as a molecule absorbs light, its energy rises to a higher excited state, and when it returns to its ground state, it produces fluorescent light. With the help of a broad-wavelength source like UV light or a narrow-wavelength source like a laser, this light is caught by charged-coupled devices (CCD). Because the wavelength of fluorescence is beyond the range of the human eye, this UV light is used to make visible light [346,347].

3.2.2. Image pre-processing

In the second important step, image enhancement is one type of pre-processing technique that is used to remove irrelevant information or noise and it is also concerned with image quality. Image size adjustment is the basic task of this technique as several sizes of images are considered for research work. Conversion of RGB images into grayscale images, binary images, and pseudo color images or vice versa is another example of image pre-processing. Contrast, brightness, spatial resolution, filters, and histogram are the common techniques of image enhancement.

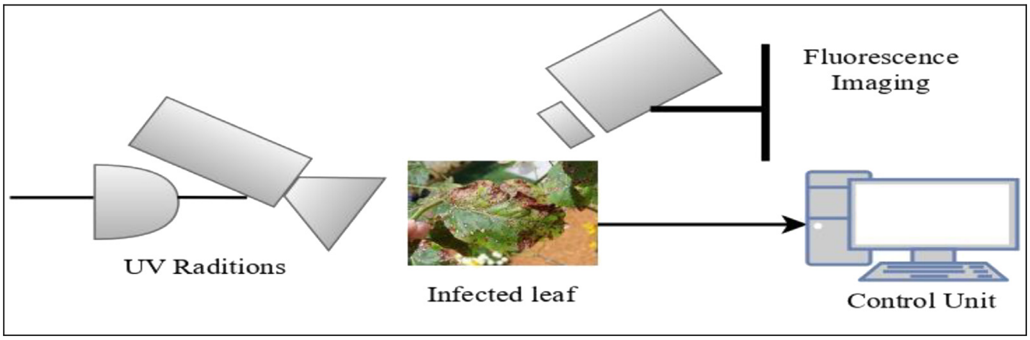


Fig. 15. The recent technique of image acquisition [334].

The term "histogram" refers to an image analysis tool that depicts the distribution of gray levels in an image as a table or graph. Contrast conducts picture detailing, giving smoothness to an object's surface and roughness to the image's backdrop surface, whilst brightness offers an image's average pixel intensity values, and spatial resolution refers to the number of pixels used to produce a digital image. Image restoration is a technique for improving image quality that differs from image enhancement in that it works with serious degradations such as sensor system distortions, bad lighting conditions, and artifacts. This method is more formal and mathematical. Image pre-processing includes image compression as well. By removing redundancies in the image, these strategies lower the amount of data required to describe the object. Essentially, this strategy is beneficial when it comes to image storage and transmission. Pre-processing a picture is critical for increasing dependability throughout the feature extraction step. Many well-known image pre-processing algorithms are considered, including the Gabor filter, CIELAB color space, Top-hat transformation, Sobel edge detector, and many others. Fogel and Dov [348] proposed the concept of the *Gabor filter* as a filtering technique that indicates the presence of any specific frequency in a localized region in a specific image direction. The 2D Gabor filter is ideal for many applications such as the recognition of words in multilingual documents, facial expression recognition, pattern analysis applications, texture analysis, IP applications namely optical character recognition, iris recognition, and fingerprint recognition, etc.

i. The other popular pre-processing approach is $L^*a^*b^*$ which is also known as *CIELAB color space* or *CIEL*$^*a^*b^*$ where L^* is lightness from black to white, a* indicates green as the negative direction to red as the positive direction and b* represents blue as the negative direction to yellow as positive direction conversion. In this technique, $L^*=0$ means darkest black, $L^*=100$ means brightest white, and $a^*=0$, $b^*=0$ the natural color is Gray. This model is used to convert RGB into CMYK color models where C indicates cyan, M indicates magenta, and Y indicates yellow in CMY models. The purpose of this model is to separate grayscale information from color information a*, b*) as this model is used in some devices like printers, cameras, and scanners [244].
ii. The *top-hat transformation* has been proposed by Gonzales (2004) which extracts elements in the image very detailed manner. The operation of this method is slightly different as it is categorized into two types, i.e., white top-hat and black top-hat transform. The white top-hat technique returns images of small objects those are also brighter than previous input images. Black top-hat transformation does the same thing, but the opposite is that the output images are darker than the previous images.
iii. In this Sobel edge detector algorithm, the image is processed one after another in x and y directions and the new image is formed by summing up the x, y edges of the image in which the Gaussian filter also plays a vital role as Sobel-X or Gx and Sobel-Y or Gy [349]. It can be identified by multiplying the 1D Gaussian filter, x-derivative, and y-derivative. Two kernels are convoluted with the original image through which the edge point is calculated, and the marked pixel is not usually considered to be a center pixel. The gradient G is then computed using the following formula and compared to the threshold value to indicate the edge of the image as following the definition $G = \sqrt{Gx^2 + Gy^2}$.
iv. SPORT (sequential pre-processing through orthogonalization) is a technique that combines many pre-processing approaches. It gathers additional data from each pre-processed dataset and combines it to increase model accuracy. The concept behind this technique is based on sequential orthogonalized partial least squares (SPOLS). The Y answers are fitted to the X1 with PLSR in the first step of this new technique, which comprises five steps. The resulting score T1 from the first stage is then used to orthogonalize X2. In the third phase, use orthogonalized X2 to predict the Y value. Steps 1,2, and 3 are performed for p different pre-processing procedures, and the outputs of all PLSR models are finally totaled up [350].
v. The author proposed a medical image-embedded encrypted watermarking technique by considering the fuzzy-based region of interest (ROI) and inverse wavelet transformation. Initially, it finds out the ROI of the original medical image through the fuzzy method. Then wavelet decomposition is performed along with singular value decomposition (SVD) on those images. Watermark images undergo 2-level Discrete Wavelet Transform (DWT) and it applies permutation on the 2nd level sub-bands. Thus, a modified watermark image is obtained where the watermarked image is obtained by performing an inverse wavelet transformation technique [351,352].
vi. The watermarking embedding procedure uses an Enhanced Suppressed Fuzzy C-Means (EnSFCM) algorithm to conclude the process with three unique classes of segmented images: Gray Matter (GM), White Matter (WM), and Cerebra-Spinal Fluid (CSF). The GM cover picture is then divided into 8 $\times$ 8 blocks, and contrast and energy are calculated to create a Fuzzy C-means (FCM) dataset. The FCM algorithm was then used to locate the blocks containing watermarks. To extract the watermark, the selected blocks are deconstructed using 2-level DWT and modified using DCT. Then, for each block of DCT blocks, calculate the correlation between mid-frequency coefficients and the pseudorandom sequences of pn0 and pn1 [353].

3.2.2.1. Data augmentation. This is a data analysis tool that operates as a regularizer by adding modified copies of existing data or by adding newly created data to expand the amount of data. This technique not only reduces the problem of overfitting in deep learning and machine learning models during training, but it also improves features like low brightness, high brightness, low contrast, high contrast, vertical flip, horizontal flip, low sharpness, high sharpness, 90-degree rotation, 180-degree rotation, 270-degree rotation, Gaussian noise, and PCA jittering, among others [354].

i. The random erasing augmentation is started with a certain probability. For image I in a mini-batch the probability is p and the unchanged probability is 1-p. Random Erasing randomly selects a rectangular region image is considered as $W \times H$ and randomly initializes the area of erasing rectangle area S_e. The aspect ratio r_e of erasing rectangle region is randomly initialized between r_1 and r_2. The size of I_e is $H_e = \sqrt{S_e \times r_e}$ and $W_e = \sqrt{\frac{S_e}{r_e}}$. Then randomly select a point $p = \left(x_{e,} y_e\right)$ from the image I. If$x_{e,} + W_e \leq W$ and $y_e + H_e \leq H$, we set the region, $I_e = (x_{e,}\ y_e, x_{e,} + W_e, y_e + H_e)$, as the selected rectangle region. Otherwise, repeat the above process until an appropriate I_e is selected. With the selected erasing region I_e, each pixel in I_e is assigned to a random value in [0, 255], respectively [355].
ii. To determine the optimal augmentation approaches, the author presented greedy breadth-first search auto augment. The first stage of this model is to locate the best augmentations based on the scoring criterion, and the second step, known as the training step, is to train the data using the best augmentations obtained in the first step. Infrastructure is employed as a black box in the searching and training process for discovering the optimal augmentation strategies and performing final classification [356].
iii. The mix-up is a recently proposed augmentation technique that generates new training samples from a linear combination of existing images and their labels (x_i, y_i) is transformed into (x_j, y_j). The samples to be combined are chosen randomly from all available images [357].
iv. Random image cropping and patches (RICAP) is also a recently proposed image augmentation technique in which a new training image is constructed from four selected images. These four images are randomly cropped and patched based on the boundary position (w, h), which are generated from a beta distribution $Beta\,(\beta, \beta)$ and set the value of $\beta = 0.3$. The coordinates $(x_k, y_k)(k = 1, 2, 3, and\, 4)$ of the upper left corners of the cropped areas are randomly selected based on the value of (w, h) such that it does not increase the image size [358].
v. *The data annotation* process is considered to build a dataset or to label a dataset in a variety of formats such as text, image, video, etc. In the case of a supervised learning method labeled data is required so that the machine can easily recognize input patterns. In picture annotation bounding box annotation, polygon annotation, semantic segmentation, landmark annotation, polyline annotation, and 3D point cloud annotation are used to obtain labeled data. This method helps to get the right prediction of the model as it is trained with the labeled input dataset [359].

3.2.3. Image segmentation

Segmentation is a process that divides the image into multiple segments or multiple regions. There are a lot of segmentation algorithms such as pixel-based or local segmentation and regional or global segmentation algorithms. To reduce the workload of image analysis, segmentation helps one step forward because the irregular presence of different leaf diseases in the image creates difficulty in obtaining accurate results of recognition. Many techniques have been utilized in image segmentation including such as thresholding, Otsu's algorithm, fuzzy C-means clustering, mean shift clustering algorithm, K-median clustering, marked watershed algorithm, K-means clustering (Kmc), and many more [360].

i. A *threshold T* [293] is used to extract the objects from the background of an image. If any point $f(x, y) > T$ this point is an object point otherwise it is a background point. There are some thresholding operations based on the value of T. If T is constant over an entire image this equation becomes global thresholding else this equation becomes variable thresholding. The histogram is a special type of tool that can solve the problem of appropriate threshold selection. On this basis the histogram can be classified into three types unimodal having one central peak, bimodal having two peaks separated by a valley, multimodal having consists of multiple peaks, where the peak is nothing but local maxima histograms. Global thresholding considers bimodal images where the histograms have two different peaks which are separated by the valley between them, and the valley point is selected by threshold T.
ii. *Otsu's algorithm* [73,74] works based on the threshold value σ_B^2/σ_T^2, where σ_T^2 represents total variance and σ_B^2 represents the difference between within-class variance and between-class variance to select an optimal threshold. This threshold value selection depends on the characteristics of the image data where the foreground and background pixels are assumed that belong to two different clusters. Let us consider that class 1 contains weight $w_1(t)$ and variance $\sigma_1^2(t)$ and class 2 contains weight $w_2(t)$ and variance $\sigma_2^2(t)$, then the weighted sum of these variances can be written as follows.

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \tag{1}$$

and the difference between within-class variance and between-class variance can be written as

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) \tag{2}$$

Here one thing is to be noted between class-variance is maximum and within class-variance is minimum. So according to this algorithm first, load the image and form the histogram. Then calculate the probability of intensities of every level and initialize $w_i(0)$, $\mu_i(0)$. Update w_i and μ_i for every threshold value and compute $\sigma_b^2(t)$ to find out the maximum variance $\sigma_b^2(t)$ for getting the optimal threshold.
iii. Bezdek [361] proposed the concept of C-means clustering named *fuzzy C-means (FCM) clustering* where first choose the number of clusters and assign weights to each data point to form clusters. This process is repeated until the algorithm produces the same result. The weight or coefficients of data points shall be changed between two iterations. Then calculate the centroid of different clusters and compute the weights of the data points to form a new cluster. The centroid of the cluster can be found by taking the mean of all data points in that cluster. The cluster will be fuzzy based for a higher value of m hyper-parameter and w_{ij} is a weight matrix that represents the degree of each element that belongs to the cluster. The purpose of the FCM is to minimize the objective function $\sum_{i=1}^{n}\sum_{j=1}^{c} w_{ij}^m \left\|x_i - c_j\right\|^2$. The concept of FCM and Kmc is almost similar, but the presence of some parameters can differentiate between the two algorithms. The large value of m and the lower value of weight w_{ij} make the clusters fuzzy whereas $m = 1$ the algorithm gives a better classification result.

iv. *The mean shift clustering algorithm* is also called the mode-seeking algorithm which has been proposed by Cheng [362], like the Kmc method but does not require the number of clusters to be specified in advance [363]. This algorithm assigns each data point iteratively to the nearest centroid of a cluster. The direction to that nearest centroid is determined based on the sample number of the points which are located on that cluster. Finally, each data point that is closer to any centroid of a cluster is assigned to that cluster.
v. *K-median clustering* is another variation of the *Kmc* algorithm which calculates the mean for each cluster to find its centroid [364]. To minimize the error in all clusters and it uses a squared 2-norm distance metric (Manhattan-distance) which calculates the median of the individual attributes based on the dataset. This clustering algorithm is reliable for discrete or binary datasets.
vi. The *watershed marker algorithm* separates the touching objects and the separation by considering the darker regions of the selected image. Zhang and Jiang [365] proposed a watershed marker algorithm based on the natural concept of water flow where the basin indicates whole or local minima, and each reservoir is separated by a watershed. In the improved watershed algorithm named *marked watershed algorithm, a* tag or point indicates the final partition of the image and provides a final segmented image by making a lowlands marker.
vii. A popular machine learning *Kmc* algorithm [20,21] calculates the centroid iteratively until it finds the optimal centroid. The data points are assigned to the cluster in such a way that the squared distance between the data points and the centroid is minimized. Initially, the number of clusters is specified, then the data points are classified, and the centroids of clusters are computed. The process will continue until the optimal centroid can be identified. So, the first sum of the squared distance is calculated between the data points and the centroid. Then assign each data point to the cluster that is closer to that data point. Finally, the centroid is calculated by taking an average of all the points of that cluster.
viii. The simple linear iterative clustering (SLIC) algorithm generates super pixels in five-dimensional spaces [labxy] where [lab] is the pixel color vector in CIELAB color space and XY is the pixel position. It uses the k-means clustering technique to generate similar regions which are called super pixels and here k represents the number of super pixels. It also controls the size of the super pixels. Initially, the input image is segmented into regular regions with k number of super pixels approximately $\frac{N}{k}$ and N is the number of pixels in the image. The dimension of each super pixel is $S \times S$ and $\sqrt{\frac{N}{k}}$. The centers of the super pixel clusters can be written as $C_k = [l_k, a_k, b_k, x_k, y_k]$. Each pixel is associated with the nearest cluster center, then update the step by adjusting the cluster centers to obtain the mean lab XY vector of all the pixels belonging to the cluster [366].

3.2.4. Feature selection and extraction

3.2.4.1. Feature selection approaches. Three popular feature selection methods have been considered for leaf disease detection like 1R feature selection, Relief-F, and correlation-based feature selection (CFS). The description of these feature selection approaches is explained as the

i. *1R feature selection method* is a powerful filter that reduces all datasets to one dataset and creates rules based on a single feature called 1-rules [367] in a dataset. It divides the dataset into training and testing and computes the accuracy of classification for each feature where higher accuracy of the classification of any feature indicates that the feature is important.
ii. *The ReliefF method* [368] is used to address binary classification problems with discrete or numerical features which evaluates the feature score for each feature to select the top score features. Each instance is selected randomly for the k-nearest neighbors of the same class and the nearest k-misses of another class. Then updates the weight of each attribute by performing the average of all hits and misses by evaluating the difference function. In case of incomplete or unknown data, the equation for this difference function can be changed.

$$W[A] := W[A] - \left(\frac{\sum_{j=1}^{k} diff(A, R_i, H_i)}{(m,k)}\right) + \left(\frac{\sum_{C=class(R_i)}\left[\frac{P(C)}{1-P(class(R_i))}\sum_{j=1}^{k} diff(A, R_i, M_i(C))\right]}{(m,k)}\right) \tag{3}$$

where $W[A]$ represents a vector of all attributes; R_i and H_i denotes as random instance and hit instance (k nearest neighbors for the same class), respectively; $M_j(C)$ and $P(C)$ represents miss instance (k nearest misses for each of other class) and probability weight for each class of misses, respectively; (m, k) are user-defined parameters, and $1 - P(class(R_i))$ is probability weight.
iii. In the *correlation-based feature selection (CFS)*, features should be highly correlated and uncorrelated with any other feature of the class and this information can be determined based on the entropy measure. Pearson correlation coefficient [298] is one type of CFS method which is a statistical measure of linear correlation between two variables. It contains a value between −1 and 1 where 0 indicates no linear correlation, −1 means negative linear correlation and +1 represents positive linear correlation. The formula for this coefficient can be written as $\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y}$, Here $\mathrm{cov}(X, Y)$ represents covariance; σ_X and σ_Y are the standard deviation of X and Y.

3.2.4.2. Feature extraction approaches. Feature extraction techniques are a form of dimensionality reduction that projects high-dimensional data to low-dimensional data for better classification and helps to overcome the curse of the dimensionality problem. Under this feature extraction step, some popular methods such as Harris corner detector, Local binary pattern, Principal component analysis (PCA), Color co-occurrence method (CCM), spatial gray level dependence matrix (SGDM), Local and Global color histogram, Complete local binary pattern (CLBP), Laws Mask, Canny edge detection, Histogram on gradient (HOG), LDA, zero algorithm and partial least square discriminant analysis (PLS-R) are explained briefly in the subsequent section.

i. *Harris corner detector* [369] is considered to detect the corners and features of an image. It calculates the spatial derivative of the grayscale image for the x, and *y*-axis. Then calculates the smallest eigenvalue of the structure tensor. Optimal results can be obtained by finding local maxima in 3 *x* 3 windows. Detection, recognition, and tracking of any objects are basic applications of this algorithm.
ii. *Local binary pattern* In the realm of computer vision, the [370] operator is employed for categorization. The feature vector divides the specified window into cells and compares each pixel in each cell to eight neighboring pixels.

If the value of the center pixel is greater than the value of the adjacent pixel, the center pixel value is set to zero. The histogram is then calculated and normalized, with normalized histograms concatenated to each pixel.

iii. *PCA* is used to perform projection or to convert data from a higher dimension to a lower dimension. For different features, the main component represents an orthogonal property that indicates a correlation of features. Projection lines must be different for distinct features due to unable to give better accuracy by using correlated or similar features in image recognition. KernelPCA (KPCA) [371] is an extension of PCA where the concept of the kernel method is used. There are many improved variants available in the literature like ISOMAP, and multilinear principal component analysis which has several additional features for extraction.

iv. The color co-occurrence technique (CCM) took three different mathematical methods into account. RGB images are transformed to HSI color space, resulting in three CCM matrices for H, S, and I, respectively. Shade, intensity, and saturation in the HSI color space [372] represent the wavelength of light, the intensity of light, and the colorful HSI space, respectively.

v. Weizheng et al. [373] proposed the spatial gray level dependence matrix (SGDM) approach for texture analysis (2008). This matrix represents a statistical method for describing the sample's form.

vi. In the *Local color histogram (LCH)* [374], the images are divided into several blocks and each pair of blocks (one block is taken from the first image, while another block is taken from the second image) is calculated separately using LCH. Finally, the total distance between two images will be added for all LCH distances.

vii. *In the Global color histogram (GCH)* [374], the histogram represents several pixels in an image graphically whereas the color histogram indicates several pixels, and different kinds of colors appear in pixels [375]. Here, color-space is discretized into n color space and the bin is created for each color. At last, several pixels are counted for all colors and stored in the histogram's bin. Euclidean distance is measured to find out similar pixels based on the color of two images where a large distance value indicates less similar images.

viii. In the c*omplete local binary pattern (CLBP)* [294], the sign of local difference (the difference between the pixel and its neighbors) is important in the LBP feature vector whereas the sign, magnitude of local difference, and the value of original center gray level are important in the CLBP feature vector. It consists of three features CLBP(S) like the original LBP, CLBP(M)which is used to determine the magnitude of the local difference, and CLBP(C) provides information on the center gray level value. Law's mask is a traditional technique for extracting and filtering images that are based on gradient operators such as Laplacians and Sobel operators by using five different masks like level, edge, spot, ripple, and wave. These sets generate twenty-five different masks, which are convolved with a texture image.

ix. *The Canny edge detection* [376] operator is used to detect the edges of an image by applying a gaussian filter to remove noise. Then it finds the intensity gradient of the image and applies the non-maximum suppression technique for the detection of edges. It also applies a double threshold technique so that weak and unconnected edges can be removed.

x. *The Histogram on gradient (HOG)* [29] used a feature descriptor (extracts important information and throws away remaining information from a selected image) to detect objects by counting occurrences of gradient orientation in a localized portion of an image. In a pre-processing step, the image is resized and calculates x gradient, y gradient by filtering the image with $[-101]$ and $[-101]^t$ kernels. Then calculates the histogram of the 8 x 8 patch of that image and a bin or number of histograms is also selected based on the direction of the gradient. The gradient of an image is sensitive to lighting. So, normalization (L2, L1 normalizations) of the histogram is required to avoid the effect of lighting. Finally, calculate the feature vector for the entire image patch.

xi. *Linear discriminant analysis (LDA)* [270] is a generalization of fisher's discriminant method which separates two groups for obtaining a maximum separation of the mean vectors of two classes. The performance of the LDA can be performed better if the distance between inter-classes is maximum and the distance between intra-classes is minimum which is defined as $s^2 = \sum_{y\in\omega_i}(y-\mu_i)^2$, where y is predicted sample, μ_i is class mean, ω_i is class and s is scatter or variance.

xii. *Zero algorithms* [377] mainly focus on target variables as it does not have prediction power and measure baseline performance.

xiii. *PLS-R* [378] is applicable when the response variable is categorical and is also used to classify hyperspectral data. The performance of PLS-R is better than other discriminatory functions and provides a good graphic representation of hyperspectral data.

3.2.5. Classification methods

Classification is a process of grouping or clustering similar data (pixels in the case of an image) with the help of labels and categorization is the ability to assign an object to a meaningful label or pattern class. There are a lot of classification algorithms under ML and DL available to classify different types of leaf disease.

3.2.5.1. Machine learning-based models. (a) Support Vector Machine (SVM)

Support vector machine [31] is a supervised learning algorithm for binary classification problems. The motivation of this algorithm is to follow the maximum margin theory principle for classification where the margin is the distance between two hyperplanes. SVM can classify linear and non-linearly separable data by converting it into a higher-dimensional space.

Advantages:

- It can perform well for structured and semi-structured datasets like text, images, etc.
- It has the capability of solving complex as it uses the kernel trick function. So it works well for high dimensional data also.
- The risk of overfitting problems is less in the case of SVM.

Limitation:

- It consumes a long time for large size of datasets.

Furthermore, famous SVM extensions such as TWSVM and MBSVM are suitable for analyzing leaf disease. TWSVM [40] explored two non-parallel hyperplanes in n-dimensional space for binary classification problems and MBSVM [33] solved a multi-class classification problem which is further investigated in many leaves' disease classification and prediction. For more variants, one can study ([379–383];[384–387])

(b) Random Forest

An example of an ensemble learning model is RF [388], which is commonly used for classification and regression issues. This algorithm can solve the problem of over-fitting and run faster to make enough decision trees. More details can be found in this study [278].

Advantages:

- This algorithm is an example of an ensemble learning technique, so it is free from overfitting problems.
- Just like SVM, it also works with high-dimensional data.
- Another feature is that it can handle binary features, numerical features, and categorical features.

Limitation:

- For large-sized data, it requires a lot of memory.

(c) Decision tree

This supervised machine learning algorithm [389] is represented in the tree structure. This model, like the CART methodology, can work with both numerical and categorical data. For categorical target data, this algorithm acts as a classifier, and for continuous target data, it acts as a regression technique. Because of its tree-like structure, this model works well without transforming data into a normalized form, making it simple to implement and human understanding easier.

Advantages:

- DT does not require scaling of data and normalization of data in the preprocessing stage.
- The presence of a missing value in the dataset has no bearing on the decision tree-building process.

Limitation:

- To train this model huge time is required.

(d) K-nearest neighbors

The non-parametric algorithm K-nearest neighbor [390] can be used for both classifications as well as regression predictive problems where k represents the total number of the nearest neighbor.

Advantages:

- For the high value of k, this method is simple to implement, versatile and has low noise sensitivity.
- It does not necessitate any prior training in order to make a forecast. As a result, new data can be added without affecting the accuracy of the results.

Limitation:

- One of the biggest downfalls is the curse of dimensionality.

3.2.5.2. Deep learning-based models. (a) Artificial neural networks (ANNs)

The ANN was suggested by psychologist Frank Rosenblatt in 1958. This model is based on the structure of the human brain, in which neurons or brain cells are replicated as artificial neurons or perceptrons [391,392].

Advantages:

- It can deal with incomplete data and has parallel processing capabilities.
- The advantage of this model is that it collects data from the whole network.

Limitation:

- This model cannot classify a nonlinearly separable dataset but better perform with the numerical dataset. As a result, before using ANN, the non-numerical problem must be converted into numerical data. The pictorial presentation of the ANN model is in Fig. 16.

(b) Multilayer perceptron's (MLP)

A multi-layer perceptron [393] is identical to a single-layer perceptron, though it has several layers hidden underneath it. This is what a deep neural network is called. It is based on a feed-forward neural network, in which each node is linked to the next.

Advantages:

- It can capture a non-linear relationship between inputs, which is one of the model's strengths.
- It works well with large input data and does quick predictions after training.
- It also provides the same accuracy value for the smaller dataset.

Limitation:

- One of the main disadvantages is the curse of dimensionality, which occurs as the total number of parameters in each layer grows. For more details, one can study Fig. 17 portrays the antistructure of the MLP model.

(c) Backpropagation neural network

Rumelhart et al. [393] proposed this modified version of the multi-layer perceptron model termed as backward propagation neural network.

Advantages:

- This adaptable methodology is quick, simple, and straightforward to deploy.
- To reduce the error weights of this model are tuned so that it can provide an efficient outcome.
- This method is flexible, and we do not need to acquire more knowledge about the network.

Limitation:

- The performance of this model for a specific problem depends on input data and it is sensitive to noisy data. One can follow Fig. 18 to understand the BP model.

(d) Convolutional neural network (CNN)

LeCun proposed the CNN Model, also known as ConvNet, in 1988 [395]. It uses images with a grid-like topology to detect and classify leaf image data. It is also focused on the feed-forward network definition [391].

Advantages:

- It can also detect images perfectly without the need for human intervention.
- It uses convolution, pooling operations and performs parameter sharing. That is why CNN models run on any device and become computationally efficient.

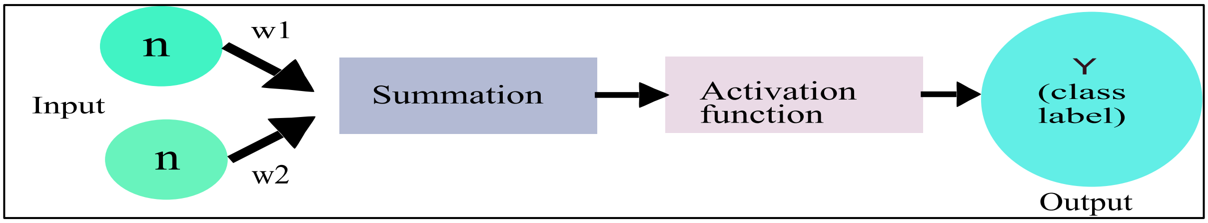


Fig. 16. Artificial neural network model [391].

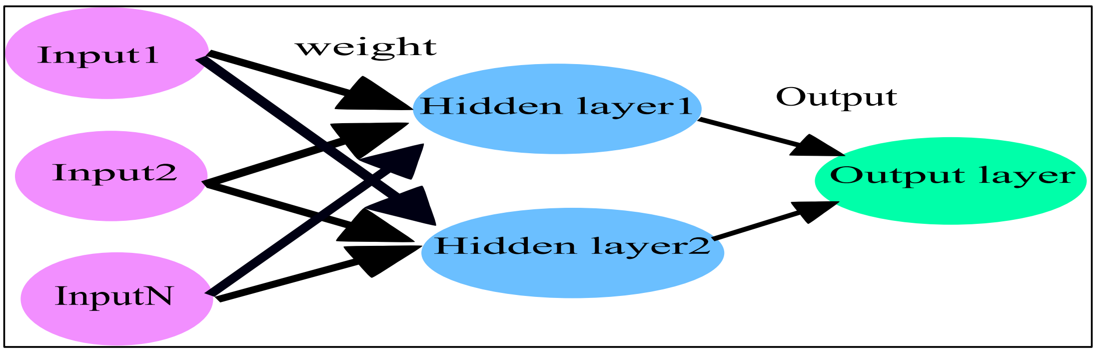


Fig. 17. Multilayer perceptron model [393].

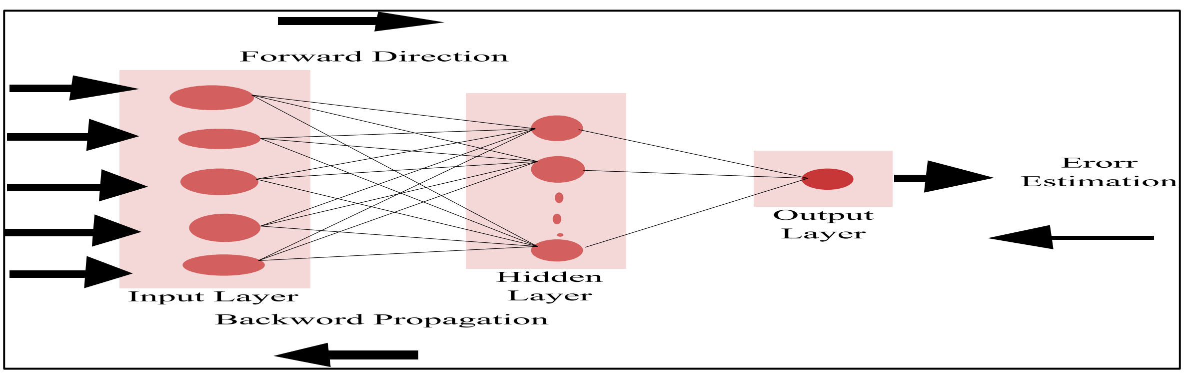


Fig. 18. Backpropagation neural network [394].

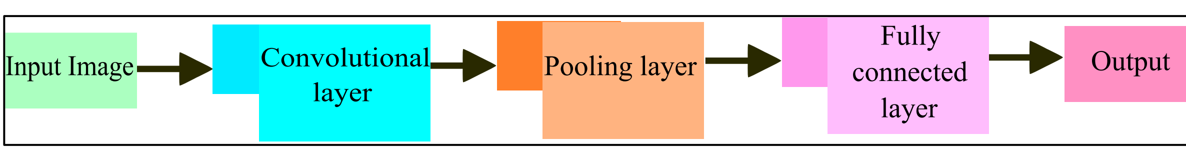


Fig. 19. Convolutional neural network [395].

Limitation:

- There are several flaws, such as the failure to encode the location of an object and the inability to detect an object in images taken from various angles. We have also drawn the architecture of CNN in Fig. 19.

(e) LeNet architecture

The LeNet (LeChun et al., 1998) are considered for feature extraction and classification. The convolution map and Max-pooling map are two steps in the feature extraction model. The convolution layer uses learnable filters to extract features from input photos. In Fig. 20, you can see a representation of the algorithm:

Advantages:

- It is simple to understand.
- It works well for character recognition images.
- The pre-processing step needs less time for ConvNet as compared to other classification models.

Limitation:

- It cannot perform well for higher resolution images and also require larger and more convolutional layers.

(f) VGG16 Model

Simonyan and Zisserman have proposed the VGG16 model in 2014 for large-scale image recognition. To distinguish image datasets, this architecture uses the same procedures as CNN, including a convolutional layer, pooling layer, fully connected

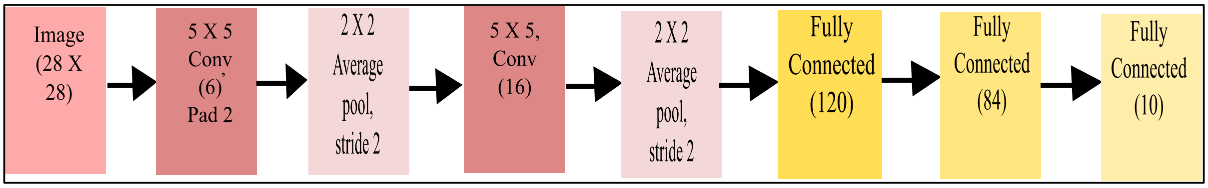


Fig. 20. CNN based LeNet architecture (LeChun et al., 1998.

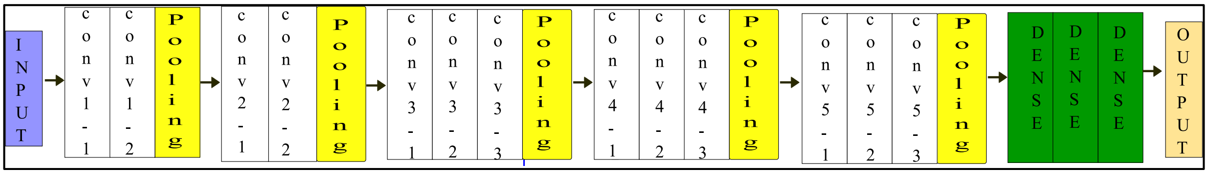


Fig. 21. Architecture of VGG16 [396].

layer with ReLU function, and an output layer with a SoftMax activation function.

Based on the classification challenge, it is one of the better performing architectures, and it has also received the localization task with some localization errors.

Advantages:

- This network is easy to implement.
- This model can be trained from the beginning with the dataset.
- This model can be initialized with pre-trained parameters then the dataset for this model can be tuned as per requirement.

Limitation:

- This model is inefficient since it needs a lot of disc space and bandwidth to train. One can follow Fig. 21 to understand the VGG16 model.

g) GoogLeNet architecture

The Google team proposed GoogLeNet architecture in 2014 in which CNN's field of inception network is the common model used for object recognition research. The GoogLeNet architecture is the initial version of the Inception model, and it is one of the three versions of the model. This model has 22 layers and uses convolutional layers with ReLU activation function, max-pooling layers, inception layer, and auxiliary classifier to do image recognition (global average pooling layer, convolutional layer, fully connected layer, and SoftMax classifier). It normally takes the size of 224 by 224 RGB photos into account.

Advantages:

- This architecture is faster than VGG.
- The size of this pre-trained model is smaller than VGG, AlexNet which is only 96 MB.

Limitation:

- It may face an overfitting problem if it has many deep layers.

(h) Learning vector quantization (LVQ)

This model [397,398] is a neural network that combines competitive learning and supervised learning features. As a classifier, this effective heuristic model is used. This network is made up of three layers: an input layer, a competitive layer, and a linear layer. An algorithm like the one below is an example.

Advantages:

- This technique creates prototypes for the respective application domain.
- The learning rate can be optimized for quick convergence.
- This approach provides a rapid, affordable, and precise way to detect a required object.

Limitation:

- The demerit of this technique is that if learning and test phases are alternated, the recognition accuracy is first improved until an optimum level is achieved. After that, with the increment of the learning rate, the accuracy starts to decrease slowly.

(i) Faster R-CNN

The Faster R-CNN [399] model is a hybrid of CNN and region proposal networks that classify objects rather than shifting the window during the classification process. Since this network is a hybrid, it combines the features of two models: CNN and region proposal networks, and it uses the CNN network's basic steps to classify objects in the image dataset (see Fig. 22).

Advantages:

- This model aids in the creation of a prototype for identifying leaf diseases.
- By adjusting the parameters in the case of images this architecture provides an appropriate classification outcome.

Limitation:

- The network's performance is adequate, but contaminated areas of a leaf cannot be perfectly segmented and classified as other diseased areas if the picture contains a shadow, which can be overcome by using the revised FCNN model.

(j) EfficientNet model

This network consists of B0 to B7 models and is made up of a group of CNN-based models with 66M parameters. The inspiration for this model came from MobileNetV2 [400]. This model [401] consists of two steps (see Fig. 23).

Advantages:

- Any new user can operate in the background using this model, which will collect input from the visual camera and promptly alert the user of the outcome, allowing the user to take preventative action sooner.

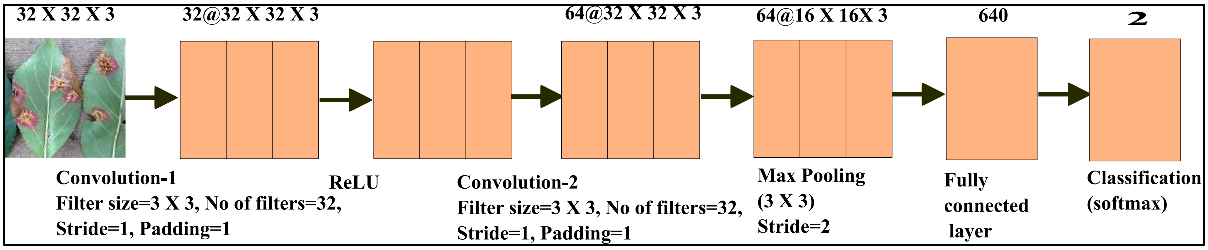


Fig. 22. Architecture of Faster R-CNN [399].

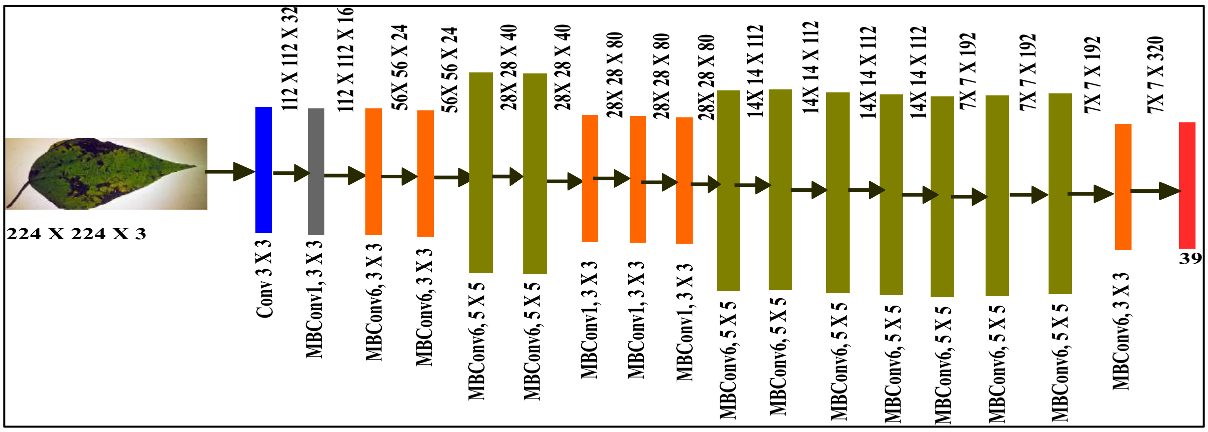


Fig. 23. Architecture of EfficientNet [401].

- Another advantage is that the number of estimated parameters does not increase as much as the model number, but accuracy does.

Limitation:

- Testing time is increased due to the network's scaled depth, width, and resolution, which is a downside of this approach. It has been discovered that scaling the network in terms of depth, width, and resolution enhances performance. Further information can be found by conducting research [259].

(k) Capsule Baseline Model

In a capsule network, a capsule is a group of neurons whose activity vector represents a specific type of entity such as an object. This model is first proposed by Geoffrey E Hinton [402].

Advantages:

- According to the results, Capsule Networks [402] can outperform other deep learning methods on complex real-world datasets.
- It can also detect diseased plants in a variety of weather and lighting circumstances, as well as from different perspectives.
- Changing the picture size, momentum, batch size, learning rate, dropout, and learning rate decay does not affect the network's performance.

Limitation:

- The Capsules have a big potential to improve agriculture, especially since researchers are working to develop the algorithm so that it can mature for actual use.

(l) Gabor Capsule Model

- The purpose of the Gabor Capsule Model [403] is to recognize blurred, deformed images and to overcome the weakness of the CNN model.

Advantages:

- Both Gabor Capsule Network and Capsule Network have the capability of recognizing unseen plant diseases under bad weather and bad illumination conditions.
- This proposed model is flexible, and convergent.
- It has fewer parameters as compared to other deep learning.

Limitation:

- Several parameters are larger than the Capsule network as it consists of approximately 10 million parameters.

(m) Fourier Convolution Neural Network (FCNN)

The authors implemented the idea of the Fourier domain in CNN [404]. It has been examined the performance of this model for larger images that are processed within variable computation time. The pooling layer of this network truncates in such a manner that spatial information throughout the whole image is retained.

Advantages

- It can shorten training time without sacrificing effectiveness.

Limitation:

- It creates boundary problems as well as information loss in the Fourier domain when it is converted from the spatial.

(n) Residual CNN

The first design combines residual learning on top of a feed-forward CNN. The second design combines the attention mechanisms and CNN's residual learning strengths. The residual

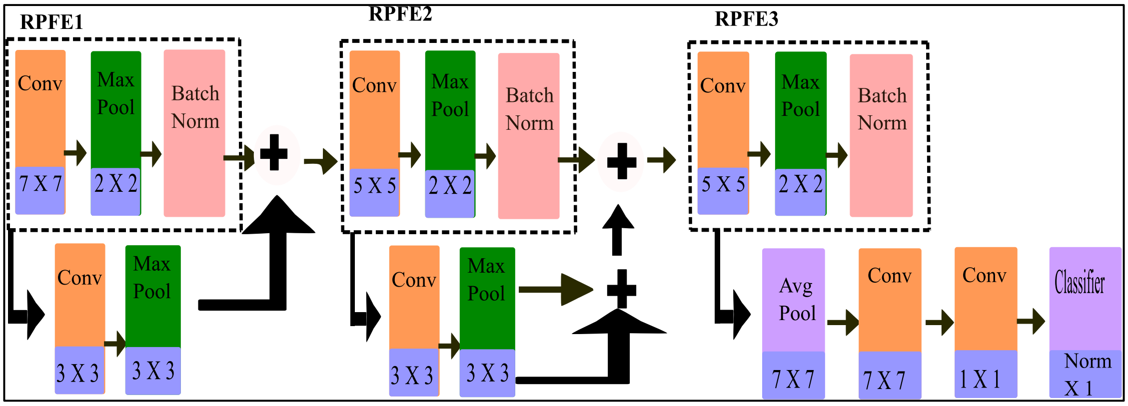


Fig. 24. Architecture of embedded Residual CNN [405].

learning-based CNN is made up of three RPFE (Residual Progressive Feature Extraction) blocks. The first RPFE block's kernel size is 7 *x* 7, the second RPFE block's kernel size is 5 *x* 5, and the final layer's kernel size is 3 *x* 3. Convolution layers and max-pooling layers follow RPFE block1 and RPFE block2. The average pooling layer and two convolution layers follow the final layer.$F(x)$ indicates the set of operations (max pooling and batch normalization) that are applied to take 'x' and $G(x)$ denotes the set of operations that skip 'x' to the next block using convolutional and max-pooling layers. Y(x) is generated by summing the individual responses of F(x) and G(x) from the residual block, as given by $Y(x) = F(x) + G(x)$. This residual CNN has at least 600 K parameters to detect the kind of infection and the number of parameters is lesser than other exiting deep learning models [405] (see Fig. 24).

Advantages:

- To detect the type of infection, this residual CNN has at least 600 K parameters, which is fewer than other existing deep learning models [405].
- Two architectures have been proposed to achieve accurate performance and low computation costs: the first architecture is used to pass significant extracted features from initial layers to deep layers of the network, and the second architecture is built on top of the RPFE architecture to learn and select prominent features from previous RPFE blocks.
- These two architectures use the attention coefficient learned to select significant characteristics and give them greater weight, then pass them on to deeper layers for more exact classification results.

Limitation:

- This embedded Residual CNN is also time-consuming architecture.

(o) SqueezeNet

This is the model proposed by [406]. A squeeze layer with 1×1 filters (decreasing input channel of 3×3 filters) and an expanded layer with a combination of 1×1 and 3×3 filters are included in this model's fire module (reducing the filter size). The ReLU layers come after the Squeeze and Expand layers. The reason for using this network is that its size is 80 times smaller than Alexnet's. As a result, to identify the presence of infection in leaves, a mobile device can load this model and recognize infected leaves (see Fig. 25).

Advantages:

- Due to its small weight, it is a good architecture as it performs deep learning operations on mobile.
- Low computational requirements.
- Another advantage is that at the time of updating the mobile application, it consumes less bandwidth and updates faster [407].

Limitation:

- Low classification accuracy and high computational complexity problems.

From the previous study, we are aware that many steps are followed to detect and identify diseases in a leaf. Among them, classification is the final step where a lot of algorithms have been implemented in this research field. As this classification step is categorized into two parts namely ML and DL techniques, various primitive as well as current methods of these techniques have been introduced. Different ML-related algorithms such as SVM, decision tree (DT), KNN, and DL algorithms like ANN, CNN, RNN, and BPNN are very well-known methods of detecting several kinds of leaf diseases by considering their pros and cons. Beyond this ensemble learning which is a collection of the same algorithms has been applied for this purpose.

4. Discussion

This section discusses the whole work done in this survey study in a brief manner. Beyond this, it illustrates the previous as well as recent processes of leaf disease detection techniques. This section also indicates that which models have been selected and which model can be chosen from machine learning and deep learning concept for leaf disease detection.

Naked-eye observations combined with routine monitoring of plant leaf stress are not only cost effective but also a time-consuming method. To address the limitations of the manual method, many computer vision and image processing techniques have been developed in recent years to identify leaf diseases. From June 2010 to December 2022, various research articles have been analyzed to determine the relevance of the study as shown in Figs. 5 and 6. This study outlines the research involved in identifying leaf diseases using various algorithms as drawn in Fig. 7. Figs. 8 and 9 are showing the statistics of the usage of several models by different government and private organizations. The description of different augmentation techniques and several performance parameters utilized for leaf disease detection are plotted in Figs. 10 and 11. Also Figs. 12 and 13 demonstrate the methodology for the classification of leaf disease using ML and DL models, while Tables 1 to 7 show different kinds of

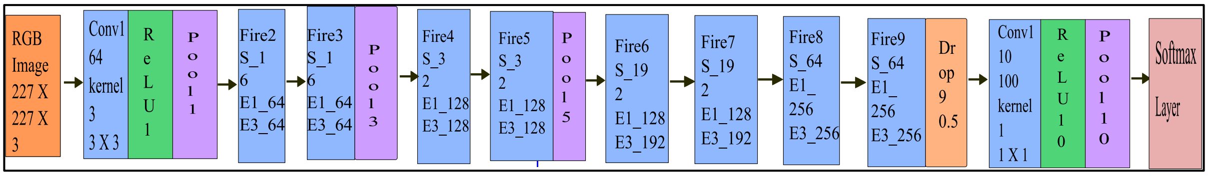


Fig. 25. Architecture of SqueezeNet [406].

images of noisy infected leaves, several leaf diseases, information about collected images of infected leaves, applied algorithms, and various output metrics. Further, the strengths and weaknesses of this research are also discussed in Section 1.6. Leaf disease classification is a step-by-step procedure in which each step is crucial for the next step and facilitates the identification of leaf stress.

In the first stage, noise reduction, smoothing, augmentation, and annotation techniques were used, while thresholding-based, histogram methods, compression methods, marked watershed methods, canny edge detection, HOG, local binary pattern (LBP), speeded up robust features (SURF), and gray-level co-occurrence matrix (GLCM) are widely applied techniques in the second step. Then, for feature selection, clustering-based methods such as k-mean clustering, k-mean clustering in the extraction process, canny edge detection, the ReliefF method, concentration factors (CFs), 1R, PSO, and genetic algorithm were considered. In the end, ML and DL algorithms such as the Naive Bayes classifier, DT, logistic regression (LR) analysis, SVM, random forest (RF), KNN, RBF, ANN, CNN, VGG-16, RNet, and variations of inception models [408] such as inceptionV3 and inceptionV4 were used. Accuracy, sensitivity, F-Score, specificity, ROC-Curve, and several other performance parameters are mentioned in Tables 5 and 6 that are used to check the effectiveness of various models in the classification of leaf disease. One can see from Figs. 10 and 11 to understand the different performance metrics in leaf disease identification and classification. The most used dataset of leaf disease detection such as PlantVillage has been captured in a variety of weather and background conditions. Furthermore, datasets such as Flavia, LeafSnap, Foliage and adrenoleukodystrophy (ALD) datasets with many binary images, grayscale images, and RGB images were used as shown in Table 7. It allows for a training of a model to classify the leaf diseases and lowers the training cost. SVM, KNN, and random forest (RF) models can be trained with at least 500–1000 images, but a broad dataset of images is recommended for the best results. To address the downside of underfitting, ANN, like CNN's deep learning concept, needs the same volume of the dataset. Both ML and DL models prefer datasets with many images. The most widely used ML and DL models are shown in Fig. 7. This 2D Pie chart illustrates that SVM has been used as a supervised learning tool with various dataset volumes most of the time. In comparison to other ML algorithms, RF and KNN models have established themselves as good performance-based classifiers. DL algorithms are also notable because they have fewer steps in the detection of leaf disease than ML-based architectures, with most of the steps being followed only in their architecture as shown in Fig. 13. Furthermore, in this field of study, ANN and CNN models are often acceptable models that can yield the desired accuracy. Consequently, the SVM model is also the most appropriate classifier and identifier. Similarly, ANN, CNN, and BPNN provide the strongest classification as well as the specific outcomes of recognition.

Recognition and classification of leaf infection is a crucial task as it is directly related to agricultural development. In earlier days manual observation and experience were the basic steps for detecting leaf diseases which were not an easy task due to the irregular presence of bacteria, fungi, and virus organisms. Computer vision, ML, DL, and image processing are the most popular applied techniques for their fast and accurate performances. Conventional machine learning, deep learning technique as well as variation of these models have given the results of leaf disease classification. The most important matter of those models is performance accuracies are varied with several image datasets. To improve predictive performance, one can consider using the ensemble learning method [409], which employs numerous learning algorithms.

5. Application challenges

The advantages and disadvantages of several algorithms have been shortly discussed in this survey work. With this discussion, it has been concluded that different models have the capabilities to provide the best result in leaf disease classification.

This literature survey has briefly explained different research studies between 2010 and 2022. It has also given basic ideas of various ML and DL-based models with their pros and cons. Detection of several diseases of the leaf using a single ML and DL-based algorithm is a critical task. Some challenges of ML and DL algorithms can be listed as follows:

Support Vector Machine (SVM):

- This powerful supervised algorithm is the most applied method as it can separate two different classes through a hyperplane. So, it can discriminate between healthy and diseased leaves of a plant at an early stage.
- Moreover, the kernel function of SVM provides a successful outcome for a non-linear dataset. Cercospora leaf spot, sugar beet rust, powdery mildew, wheat leaf rust, leaf spot disease on pear fruit, yellow rust, septoria, etc are all these infectious organisms that are perfectly identified by this statistical method.
- Most of the leaf diseases can be detected by this algorithm but for all diseases, it always cannot provide the highest classification accuracy due to the nature of those infections that cannot be identified perfectly.

Random Forest

• This statistical learning is frequently used for identifying several diseases of the leaf. This algorithm is made up of several decision trees or other algorithms so, it consists of features of ensemble learning, and based on this it classifies distinct leaf diseases with the significant outcome. It generates low bias, and low variance forest and works with an imbalanced dataset. The performance of this model is faster as it works with a subset of features.

- RF provides the best classification result in classifying Leaf spots, red palm weevils, rhizopus Rot, leaf spot, and pink diseases. It deals with many decision trees, so it fails to understand the significance of each variable or feature. That is why it cannot provide classify all diseases correctly.

Decision tree

- This algorithm has also been considered for identifying leaf disease and it has achieved a perfect result as per its performance.
- Providing less effort for data preprocessing this model can be trained but the limitation is it consumes too much time for training.

K nearest neighbor

- This machine algorithm also is allowed frequently like a random forest for classifying leaf disease. It can learn the leaf dataset and provide predicted results as fast as possible.
- This model fails to produce accurate results for many healthy as well as diseased leaves because the cost of computing the distance between the new point and each old point is high, degrading the algorithm's performance. For the most part, machine learning works effectively with structured data. Due to the existence of noise and missing values in a structured leaf dataset, the KNN algorithm may not deliver reliable results.

Artificial neural network

- There is a collection of interconnected neurons in ANN arranged in a row and each neuron contains values from 0.1 to 1 where 0.1 is the darkest pixel and 1 is the lightest pixel, using this concept ANN can classify several diseases of a leaf.
- Less amount of information for doing classification may not affect this network to obtain an accurate result. So, this network can be selected for detecting and classifying leaf diseases.
- One of the major limitations is it cannot perform well for real-world images outside the dataset. Another drawback is many annotated datasets are unavoidable for this network.

Multilayer perceptron

- MLP consists of at least three layers an input layer, a hidden layer, and an output layer with neurons that use non-linear functions to separate non-linear data. It also uses a supervised learning technique called the back propagation technique to generate such weight value for which predict outcome becomes as same as the actual output, this is the working principle of MLP and in this way, it classifies disease perfectly.
- Spatial information is degraded by this model. Spatial features contain this kind of information that can help to match objects (disease). That is why the classification process is hampered.

Backpropagation neural network

- It performs classification by taking the facility of chain and power rules that allows backpropagation to function with any number of outputs and using less information on infected and healthy leaf images it obtains a successful outcome.
- The performance of this algorithm depends on input data specifically the presence of noise, missing data in input data generates difficulty to obtain a significant result.

Convolutional neural network

- The connection between each and every neuron in the neural network generates an overfitting problem which can be overcome by CNN as a neuron in a layer is connected to a small region of the layer. It can automatically detect important features for classifying several diseases of leaves and for obtaining similar outcomes it can share weights among neurons. That is why performance is accurate and faster. Melon yellow spot virus, zucchini yellow mosaic virus, black Sigatoka, tea red leaf spot, tea leaf blight, and tea red scab are several diseases that have been successfully classified by this network, and its updated networks.
- The limitation of this algorithm is the identification issue of the position and orientation of infectious organisms in a leaf, that is why in some research studies it cannot provide a successful result. Invariance helps CNN to recognize important features of an image, CNN is unable to do this thing own.

Advanced Deep Learning Models

- LeNet architecture: - Selection of higher resolution images provide an inappropriate outcome.
- VGG16 model: -Adequate system configuration is required for this model.
- GoogLeNet architecture: - A huge number of convolution layers generate an overfitting problem.
- LVQ model: -Increment in learning rate reduces classification accuracy.
- Faster R-CNN: -This model is unable to segment the images of cluttered areas in infected leaves.
- EfficientNet model: - Scaled depth, width, and resolution of the network increase the computation time of testing dataset.
- Capsule Baseline model: -For practical implementation this model is required to improve.
- Gabor Capsule model: -A huge number of parameters is the main issue of this model.
- FCNN: -Spatial information of data may not be present for a particular point of this model.
- Residual CNN: - This is one of the time-consuming processes.
- SqueezeNet: - Classification accuracy is low and has high computation time.

So, this section clearly illustrates the challenges related to ML and DL models for leaf disease detection. As per the popularity of the ML approach, the SVM is the best performer to classify the leaf disease over other ML models and in the DL analysis, the high number of resources is the biggest challenge. However, the CNN model is performing superior in comparison to the other deep learning models, nowadays, researchers are interested in an ensemble or hybrid approach for better performance.

6. Conclusion and future work

Several ML and DL models attempt to identify leaf diseases, but some challenges remain present in this context. Many published research studies have worked with pre-trained models such as GoogLeNet, AlexNet, VGGNet, and ResNet, and their training data such as ImageNet [410,411] (Image Database) which have produced better accuracy in comparison to other existing models. Although the most common PlantVillage dataset is adequate to train the CNN model, some researchers have used less than 1,000 original images in their research and used artificial expansion techniques including data augmentation such as rotation, translation, cropping, grayscale conversion, and so on to boost efficiency. The key issue is that models suffer from under-fitting and are unable to accurately predict various leaf diseases due to a scarcity of training data. Because of the small dataset and the constraints of the hardware, augmentation and annotation techniques may help to solve the issue. Due to the higher cost of graphical processing units (GPUs), it is not feasible for small organizations to deal with high dimensional and complex datasets. A parallel computing platform like compute unified device architecture (CUDA) allows developers to improve computing performance while performing the classification on large datasets. Another challenge for a DL model is to determine the size of layers and neurons for producing an optimal result in the case of unknown detection. A large training dataset adds to the difficulty of learning a model, but this disadvantage can be overcome by using a dimensional reduction technique called PCA, which is nothing more than a technical feature extraction. The features were chosen to avoid being correlated, but the existing correlation between them adds to the model's complexity. This inadequacy can be solved by integrating PCA and independent component analysis (ICA) approaches, which can remove feature correlation, and reduce feature dimensionality, and recognition complexity. Some researchers have implemented hyperspectral images of crops and leave to detect stress, pest, mites, weeds, and contaminants. With the help of support vector ML-based models, these hyperspectral images have shown impressive outcomes, but CNN networks can be one of the better options to enhance efficiency using hyperspectral images. DL models are also prone to over-fitting, which results in inappropriate classification. To solve this flaw, hyper-parameters such as drop-out and regularization models can be fine-tuned. VGG16, VGG19, AlexNet, and GoogLeNet have also been commonly used, and their output has been compared using various leaf datasets. There are many baseline models including SVM, Multiclass SVM, KNN, RF, KMC, DT, ANN, CNN, a variant of RNet, BPNN, DNet with 121, DCNN with NAG, LeafNet, updated Faster R-CNN, VGG-FCN-VD16, VGG-FCN-S, and Faster R-CNN which are considered for leaf disease prediction and attained success rates of detection. According to the survey, SVM has been heavily considered for this purpose because of its simplistic design and ability to provide an ideal global solution. When data samples cannot be adequately separated, kernel functions such as polynomial, and RBF provide a high dimensional conversion feature to SVM. ANN also produces a powerful result where the problem causes an optimal local outcome. This can be surpassed by an excessive amount of data. Researchers have rarely adopted augmentation techniques such as resizing, color conversion, cropping, and so on for machine learning classifiers, which can provide extra support for successful classification. Likewise, the use of data annotation in the context of the deep learning approach is not uncommon in this field of research. Many challenges can be further explored

1. As we know that leaf can be infected with more than one disease. However, focusing on only one disease and the rest is not being addressed properly. This topic is seldom explored in the literature. As a result, this is becoming a challenging task.
2. Most of the research experiments in the field of leaf disease detection have been done with available datasets, such as PlantVillage, Flavia, and others, which contain thousands of different images of plants, however, high dimensional dataset in this field is still required.
3. For their study, many researchers have used hyperspectral, thermal, and multispectral images of the leaf. Some researchers have proposed their research work such as 2D CNN and 3D CNN, using these types of images, and these models have also shown substantial results. As a result, CNN can be thought of as having an early detection function for those images but still scope for better performances.
4. Another important challenge is the recognition of new variants of leaf disease because the life cycles of infectious organisms of all plants may vary However, conventional steps will not be helpful in this regard.

From the future perspective, there is an urgent requirement to study more infected leaves that may be affected by more than one disease at a time and attained the best solution for this problem. The primary and derived models SVM, BPNN, KNN, DNet with 121 layers, and CNN classifiers were found to have better generalization ability in this study. SVM is the mostly used machine learning algorithm like MTSVM, while CNN and ANN algorithms are considered DL algorithms. The efficiency of leaf disease detection can be checked by combining the most used algorithms with another newly improved algorithm. A semi-supervised learning approach which is somehow a hybrid approach of supervised and unsupervised learning, can be explored for detecting leaf disease and boost up the classification performance. An application for a mobile system should be developed to assist in the capturing of images of diseases such as leaves, fruit, and vegetables. Thus, the farmer will get more profit because of being able to accurately recognize the symptoms of leaf diseases before using chemical pesticides. Furthermore, future work will be conducted on larger land areas and will include combined aerial images which are taken by drone cameras to assess the efficiency of the various models. Current feature extraction, feature selection, and segmentation algorithms can all be tweaked to produce better-extracted, segmented, and uncorrelated features. The addition of several data augmentation techniques in the deep learning approach can affect the performance of the model. Hybrid deep learning models based on densely connection inception convolutional neural network (DENSE-INCEP) [412], VGG-FCN-S, and VGG-FCN-VD16 have recently been implemented in the research field of leaf disease detection and have effectively classified different leaf stress patterns. Thus, it is one of the future directions that one can combine the machine learning model with other models to improve the performance of the hybrid model and using combined learning algorithms can result in higher accuracy. An adjoint approach that is a combination of different architectures is a newly adopted concept that has been already applied in many research works ([413]). The various kinds of deep learning-based adjoint approaches obtain significant outcomes so they become popular. From the research study, it has been observed that this idea based on deep learning or machine learning has not been implemented recently. So, the adjoint approach may provide a better way in this research study ([414]).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] John P. Damicone, Brandenberger Lynn, Common Diseases of Tomatoes: Part II. Diseases Caused By Bacteria, Viruses, and Nematodes, Oklahoma Cooperative Extension Service, Division of Agricultural Sciences and Natural Resources -Oklahoma State University, 2015.
[2] Juan Ignacio Arribas, Gonzalo V. Sánchez-Ferrero, Gonzalo Ruiz-Ruiz, Jaime Gómez-Gil, Leaf classification in sunflower crops by computer vision and neural networks, Comput. Electron. Agric. 78 (1) (2011) 9–18.
[3] Sunil S. Harakannanavar, Jayashri M. Rudagi, Veena I. Puranikmath, Ayesha Siddiqua, R. Pramodhini, Plant leaf disease detection using computer vision and machine learning algorithms, Glob. Transitions Proc. 3 (1) (2022) 305–310.
[4] Federico Martinelli, Scalenghe Riccardo, Davino Salvatore, Panno Stefano, Scuderi Giuseppe, Ruisi Paolo, Villa Paolo, et al., Advanced methods of plant disease detection. A review, Agron. Sustain. Dev. 35 (1) (2015) 1–25.

[5] Arti N. Rathod, Bhavesh Tanawal, Vatsal Shah, Image processing techniques for detection of leaf disease, Int. J. Adv. Res. Comput. Sci. Softw. Eng. 3 (11) (2013).
[6] Sachin D. Khirade, A.B. Patil, Patil plant disease detection using image processing, in: 2015 International Conference on Computing Communication Control and Automation, IEEE, 2015, pp. 768–771.
[7] Alan C. Bovik, Handbook of Image and Video Processing, Academic Press, 2010.
[8] Andrew Crane-Droesch, Machine learning methods for crop yield prediction and climate change impact assessment in agriculture, Environ. Res. Lett. 13 (11) (2018) 114003.
[9] Daniel P. Bebber, Climate change effects on Black Sigatoka disease of banana, Phil. Trans. R. Soc. B 374 (1775) (2019) 20180269.
[10] Muhammad Naveed Afzal, Tariq Muhammad, Ahmed Muhammad, Abbas Ghulam, Mehmood Zahid, Managing planting time for cotton production, in: Cotton Production and Uses, Springer, Singapore, 2020, pp. 31–44.
[11] Rafael Faria Caldeira, Wesley Esdras Santiago, Barbara Teruel, Identification of cotton leaf lesions using deep learning techniques, Sensors 21 (9) (2021) 3169.
[12] Dilshad Ahmad, Afzal Muhammad, Climate change farm based autonomous adaptation measures and its impact on wheat crop productivity in Punjab, Pakistan, 2022.
[13] Steven A. Wakelin, Gomez-Gallego Mireia, Jones Eirian, Smaill Simeon, Lear Gavin, Lambie Suzanne, Climate change induced drought impacts on plant diseases in New Zealand, Australas. Plant Pathol. 47 (1) (2018) 101–114.
[14] Serge Savary, Laetitia Willocquet, Sarah Jane Pethybridge, Paul Esker, Neil McRoberts, Andy Nelson, The global burden of pathogens and pests on major food crops, Nat. Ecol. Evol. 3 (3) (2019) 430–439.
[15] P. Juroszek, P. Racca, S. Link, J. Farhumand, B. Kleinhenz, Overview on the review articles published during the past 30 years relating to the potential climate change effects on plant pathogens and crop disease risks, Plant Pathol. 69 (2) (2020) 179–193.
[16] David M. Rizzo, Lichtveld Maureen, A.K. Mazet Jonna, Eri Togami, Sally A. Miller, Plant health and its effects on food safety and security in a one health framework: Four case studies, One Health Outlook 3 (1) (2021) 1–9.
[17] Rachel Grabka, Tyler W. d'Entremont, Sarah J. Adams, Allison K. Walker, Joey B. Tanney, Pervaiz A. Abbasi, Shawkat Ali, Fungal endophytes and their role in agricultural plant protection against pests and pathogens, Plants 11 (3) (2022) 384.
[18] Stephan Dreiseitl, Lucila Ohno-Machado, Logistic regression and artificial neural network classification models: a methodology review, J. Biomed. Inform. 35 (5–6) (2002) 352–359.
[19] Dheeb Al Bashish, Malik Braik, Sulieman Bani-Ahmad, Detection and classification of leaf diseases using K-means-based segmentation and, Inf. Technol. J. 10 (2) (2011) 267–275.
[20] Haiguang Wang, Guanlin Li, Zhanhong Ma, Xiaolong Li, Image recognition of plant diseases based on backpropagation networks, in: 2012 5th International Congress on Image and Signal Processing, IEEE, 2012, pp. 894–900.
[21] Ming Wang, Jianbing Yan, Jiuran Zhao, Wei Song, Xiaobo Zhang, Yannong Xiao, Yonglian Zheng, Genome-wide association study (GWAS) of resistance to head smut in maize, Plant Sci. 196 (2012) 125–131.
[22] Siddharth Singh Chouhan, Kaul Ajay, Uday Pratap Singh, Sanjeev Jain, Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology, IEEE Access 6 (2018) 8852–8863.
[23] Md Sultan Mahmud, Qamar U. Zaman, Travis J. Esau, Young K. Chang, Gordon W. Price, Balakrishnan Prithiviraj, Real-Time Detection of Strawberry Powdery Mildew Disease Using a Mobile Machine Vision System, Agronomy 10 (7) (2019) 1027.
[24] Tan Nhat Pham, Ly Van Tran, Son Vu Truong Dao, Early disease classification of mango leaves using feed-forward neural network and hybrid metaheuristic feature selection, IEEE Access 8 (2020) 189960-189973.
[25] Shohreh Liaghat, Reza Ehsani, Shattri Mansor, Helmi Z.M. Shafri, Sariah Meon, Sindhuja Sankaran, Siti H.M.N. Azam, Early detection of basal stem rot disease (Ganoderma) in oil palms based on hyperspectral reflectance data using pattern recognition algorithms, Int. J. Remote Sens. 35 (10) (2014) 3427–3439.
[26] S.W. Zhang, Y.J. Shang, L. Wang, Plant disease recognition based on plant leaf image, J. Anim. Plant Sci. 25 (3) (2015) 42–45.
[27] F. Jakjoud, A. Hatim, A. Bouaddi, Detection of diseases on tomato leaves based on subclassifiers fuzzy combination, Int. J. Innov. Technol. Explor. Eng. (IJITEE) (ISSN: 2278-3075) (2019).
[28] Oktaviana Rena Indriani, Edi Jaya Kusuma, Christy Atika Sari, Eko Hari Rachmawanto, Tomatoes classification using K-NN based on GLCM and HSV color space, in: 2017 International Conference on Innovative and Creative Information Technology, ICITech, IEEE, 2017, pp. 1–6.
[29] K. Suganya Devi, P. Srinivasan, Bandhopadhyay Sivaji, H2K–A robust and optimum approach for detection and classification of groundnut leaf diseases, Comput. Electron. Agric. 178 (2020) 105749.
[30] Swati Singh, Isha Gupta, Sheifali Gupta, Deepika Koundal, Sultan Aljahdali, Shubham Mahajan, Amit Kant Pandit, Deep learning based automated detection of diseases from apple leaf images, CMC-Comput. Mater. Continua 71 (1) (2022) 1849–1866.
[31] Corinna Cortes, Vapnik Vladimir, Support-vector networks, Mach. Learn. 20 (3) (1995) 273–297.
[32] T. Rumpf, A.-K. Mahlein, U. Steiner, E.-C. Oerke, H.-W. Dehne, L. Plümer, Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance, Comput. Electron. Agric. 74 (1) (2010) 91–99.
[33] Zhi-Xia Yang, Yuan-Hai Shao, Xiang-Sun Zhang, Multiple birth support vector machine for multi-class classification, Neural Comput. Appl. 22 (1) (2013) 153–161.
[34] Manisha Bhange, H.A. Hingoliwala, Smart farming: Pomegranate disease detection using image processing, Procedia Comput. Sci. 58 (2015) 280–288.
[35] Md Rasel Mia, Sujit Roy, Subrata Kumar Das, Md Atikur Rahman, Mango leaf disease recognition using neural network and support vector machine, Iran J. Comput. Sci. 3 (3) (2020) 185–193.
[36] Ganesh Bhadur, Rajneesh Rani, Agricultural crops disease identification and classification through leaf images using machine learning and deep learning technique: A review, in: Proceedings of the International Conference on Innovative Computing & Communications, ICICC, 2020.
[37] Lars Kai Hansen, Peter Salamon, Neural network ensembles, IEEE Trans. Pattern Anal. Mach. Intell. 12 (10) (1990) 993–1001.
[38] Javaid Ahmad Wani, Sharma Sparsh, Muzamil Malik, Ahmed Suhaib, Sharma Surbhi, Singh Saurabh, Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges, Arch. Comput. Methods Eng. (2021) 1–37.
[39] Stefan Thomas, Behmann Jan, Rascher Uwe, Mahlein Anne-Katrin, Evaluation of the benefits of combined reflection and transmission hyperspectral imaging data through disease detection and quantification in plant–pathogen interactions, J. Plant Dis. Prot. (2022) 1–16.
[40] Khemchandani Reshma Jayadeva, Chandra Suresh, Twin support vector machines for pattern classification, IEEE Trans. Pattern Anal. Mach. Intell. 29 (5) (2007) 905–910.
[41] Divya Tomar, Sonali Agarwal, A comparison on multi-class classification methods based on least squares twin support vector machine, Knowl.-Based Syst. 81 (2015) 131–147.
[42] Scindhiya Laxmi, S.K. Gupta, Multi-category intuitionistic fuzzy twin support vector machines with an application to plant leaf recognition, Eng. Appl. Artif. Intell. 110 (2022) 104687.
[43] Huang Guang-Bin, Qin-Yu Zhu, Chee-Kheong Siew, Extreme learning machine: theory and applications, Neurocomputing 70 (1-3) (2006) 489–501.
[44] Anshul Bhatia, Anuradha Chug, Amit Prakash Singh, Application of extreme learning machine in plant disease prediction for highly imbalanced dataset, J. Stat. Manag. Syst. 23 (6) (2020) 1059–1068.
[45] Raj Kumar, Anuradha Chug, Amit Prakash Singh, Singh Dinesh, A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a review, J. Sensors 2022 (2022).
[46] Umesh Gupta, Deepak Gupta, Regularized based implicit Lagrangian twin extreme learning machine in primal for pattern classification, Int. J. Mach. Learn. Cybern. 12 (5) (2021) 1311–1342.
[47] Bikash Chawal, Prasad Panday Sanjeev, Rice plant disease detection using twin support vector machine (TSVM), J. Sci. Eng. 7 (2019) 61–69.
[48] T.S. Poornappriya, R. Gopinath, Rice plant disease identification using artificial intelligence approaches, 2022.
[49] Y. LeCun, Y. Bengio, in: M.A. Arbib (Ed.), The Handbook of Brain Theory and Neural Networks, MIT Press, 1995, (Chapter Convolutional networks for images, speech, and time-series).
[50] Yann LeCun, Lon Bottou, Yoshua Bengio, Patrick Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86 (11) (1998) 2278–2324.
[51] Yusuke Kawasaki, Hiroyuki Uga, Satoshi Kagiwada, Hitoshi Iyatomi, Basic study of automated diagnosis of viral plant diseases using convolutional neural networks, in: International Symposium on Visual Computing, Springer, Cham, 2015, pp. 638–645.
[52] Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, Ruslan R. Salakhutdinov, Improving neural networks by preventing co-adaptation of feature detectors, 2012, arXiv preprint arXiv:1207.0580.
[53] Mads Dyrmann, Henrik Karstoft, Henrik Skov Midtiby, Plant species classification using deep convolutional neural network, Biosyst. Eng. 151 (2016) 72–80.
[54] Weibo Liu, Zidong Wang, Xiaohui Liu, Nianyin Zeng, Yurong Liu, Fuad E. Alsaadi, A survey of deep neural network architectures and their applications, Neurocomputing 234 (2017) 11–26.

[55] Jinzhu Lu, Tan Lijuan, Jiang Huanyu, Review on convolutional neural network (CNN) applied to plant leaf disease classification, Agriculture 11 (8) (2021) 707.
[56] Konstantinos P. Ferentinos, Deep learning models for plant disease detection and diagnosis, Comput. Electron. Agric. 145 (2018) 311–318.
[57] L. Annabel, Sherly Puspha, T. Annapoorani, P. Deepalakshmi, Machine learning for plant leaf disease detection and classification–A review, in: 2019 International Conference on Communication and Signal Processing, ICCSP, IEEE, 2019, pp. 0538–0542.
[58] Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta, ToLeD: Tomato leaf disease detection using convolution neural network, Procedia Comput. Sci. 167 (2020) 293–301.
[59] Jay Trivedi, Yash Shamnani, Ruchi Gajjar, Plant leaf disease detection using machine learning, in: International Conference on Emerging Technology Trends in Electronics Communication and Networking, Springer, Singapore, 2020, pp. 267–276.
[60] Xibei Huang, Aibin Chen, Guoxiong Zhou, Xin Zhang, Jianwu Wang, Ning Peng, Na Yan, Canhui Jiang, Tomato leaf disease detection system based on FC-SNDPN, Multimedia Tools Appl. 82 (2) (2023) 2121–2144.
[61] Syeda Khadizatul Maria, Shahrun Siddique Taki, Md Mia, Biswas Al Amin, Majumder Anup, Hasan Firoz, Cauliflower disease recognition using machine learning and transfer learning, in: Smart Systems Innovations in Computing, Springer, Singapore, 2022, pp. 359–375.
[62] Anil Bhujel, Khan Fawad, Kumar Basak Jayanta, Jaihuni Mustafa, Sihalath Thavisack, Moon Byeong-Eun, Park Jaesung, Kim Hyeon-Tae, Detection of gray mold disease and its severity on strawberry using deep learning networks, J. Plant Dis. Prot. (2022) 1–14.
[63] Shunping Ji, Chi Zhang, Anjian Xu, Yun Shi, Duan Yulin, 3D convolutional neural networks for crop classification with multi-temporal remote sensing images, Remote Sens. 10 (1) (2018) 75.
[64] G. Sambasivam, Opiyo Geoffrey Duncan, A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks, Egypt. Inform. J. 22 (1) (2021) 27–34.
[65] Sathian Dananjayan, Yu Tang, Jiajun Zhuang, Chaojun Hou, Shaoming Luo, Assessment of state-of-the-art deep learning based citrus disease detection techniques using annotated optical leaf images, Comput. Electron. Agric. 193 (2022) 106658.
[66] Saumya Yadav, Neha Sengar, Akriti Singh, Anushikha Singh, Malay Kishore Dutta, Identification of disease using deep learning and evaluation of bacteriosis in peach leaf, Ecol. Inform. 61 (2021) 101247.
[67] Asif Iqbal Khan, S.M.K. Quadri, Saba Banday, Junaid Latief Shah, Deep diagnosis: A real-time apple leaf disease detection system based on deep learning, Comput. Electron. Agric. 198 (2022) 107093.
[68] Dhruvil Shah, Vishvesh Trivedi, Vinay Sheth, Aakash Shah, Uttam Chauhan, ResTS: Residual deep interpretable architecture for plant disease detection, Inf. Process. Agric. 9 (2) (2022) 212–223.
[69] Fraol Gelana Waldamichael, Girma Debelee Taye, Megersa Ayano Yehualashet, Coffee disease detection using a robust HSV color-based segmentation and transfer learning for use on smartphones, Int. J. Intell. Syst. (2011).
[70] Coffee disease dataset, 2021, Available at: https://github.com/esgario/lara2018/. (Accessed April 2021).
[71] Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, Faster r-cnn: Towards real-time object detection with region proposal networks, IEEE Trans. Pattern Anal. Mach. Intell. 39 (6) (2016) 1137–1149.
[72] Gensheng Hu, Haoyu Wu, Yan Zhang, Mingzhu Wan, A low shot learning method for tea leaf's disease identification, Comput. Electron. Agric. 163 (2019) 104852.
[73] Nilay Ganatra, Atul Patel, A multiclass plant leaf disease detection using image processing and machine learning techniques, Int. J. Emerg. Technol. 11 (2) (2020) 1082–1086.
[74] Nilay Ganatra, Atul Patel, Performance analysis of fine-tuned convolutional neural network models for plant disease classification, Int. J. Control Autom. 13 (3) (2020) 293–305.
[75] Haixia Qi, Yu Liang, Quanchen Ding, Jun Zou, Automatic identification of peanut-leaf diseases based on stack ensemble, Appl. Sci. 11 (4) (2021) 1950.
[76] Mehdhar S.A.M. Al-gaashani, Shang Fengjun, S.A. Muthanna Mohammed, Khayyat Mashael, A. Abd El-Latif Ahmed, Tomato leaf disease classification by exploiting transfer learning and feature concatenation, IET Image Process. (2022).
[77] Deepak Gupta, Ambika Choudhury, Umesh Gupta, Priyanka Singh, Mukesh Prasad, Computational approach to clinical diagnosis of diabetes disease: a comparative study, Multimedia Tools Appl. (2021) 1–26.
[78] Deepak Gupta, Barenya Bikash Hazarika, Mohanadhas Berlin, Usha Mary Sharma, Kshitij Mishra, Artificial intelligence for suspended sediment load prediction: a review, Environ. Earth Sci. 80 (9) (2021) 346.
[79] R.H. Stover, Disease management strategies and the survival of the banana industry, Annu. Rev. Phytopathol. 24 (1) (1986) 83–91.
[80] Douglas H. Marin, Ronald A. Romero, Mauricio Guzmán, Turner B. Sutton, Black sigatoka: an increasing threat to banana cultivation, Plant Dis. 87 (3) (2003) 208–222.
[81] Scott Nelson, Black Leaf Streak of Banana, Cooperative Extensive Service, 2008, pp. 1–10, [online], Available (2021): http://www.ctahr.hawaii.edu/oc/freepubs/pdf/PD-50.pdf.
[82] D. Ezra, T. Gat, Y. Skovorodnikova, Y. Vardi, Kosto I., First report of Alternaria black spot of pomegranate caused by Alternaria alternate in Israel, Australas. Plant Dis. Notes 5 (1) (2010) 1–2.
[83] Black spot, 2021, [online], Available: https://www.familyhandyman.com.
[84] A.K. Misra, P.K. Shukla, B.K. Pandey, Diseases of mango, in: A.K. Misra, P. Chowdappa, P. Sharma, R.K. Khetrapal (Eds.), Diseases of Fruit Crops, Indian Phytopathological Society, New Delhi, 2012, pp. 278–335, 342p., Disponible enlínea: https://www.researchgate.net/publication/311886856_Diseases_of_Mango.
[85] Joseph Obrien, SootyMold, USDA Forest Service, 2021, [online], Available: https://www.bioadvance.service.
[86] R.D. Fitzell, C.M. Peak, The epidemiology of anthracnose disease of mango: inoculum sources, spore production and dispersal, Ann. Appl. Biol. 104 (1) (1984) 53–59.
[87] Anthracnose: What are the symptoms and how to treat it, 2021, Revolutionary Plant Health Solutions, [online] Available (2021): https://www.arborjetcom.
[88] Paul Taylor, Kurt Lindbeck, Weidong Chen, Rebecca Ford, Lentil diseases, in: Lentil, Springer, Dordrecht, 2007, pp. 291–313.
[89] Thomas J. Gulya, Febina Mathew, Robert Harveson, Samuel Markell, Charles Block, Block Charles Diseases of Sunflower, Springer International Publishing Switzerland, 2016, [online], Available(2021): https://www.Link.springer.com.
[90] Andrew Friskop, Samuel G. Markell, Tom Gulya, Downy Mildew of Sunflower, NDSU Extension Service N.D. Agricultural Experiment Station, 2009.
[91] Downy Mildew, Planet Natural Research Center, 2021, [online], Available: https://www.planetnatural.com.
[92] John Weiland, Georg Koch, Sugarbeet leaf spot disease (Cercosporabeticola Sacc), Mol. Plant Path. 5 (3) (2004) 157–166.
[93] Dan Egel, Cercospora Leaf Spot of Beet, Purdur University, 2017, [online], Available (2021): http://www.vegcropshotline.org.
[94] Sylvain Lerat, Anne-Marie Simao-Beaunoir, Carole Beaulieu, Genetic and physiological determinants of *Streptomyces scabies* pathogenicity, Mol. Plant Path. 10 (5) (2009) 579–585.
[95] Bonnie L Grant, Scabon vegetables – How to treat scab disease in the vegetable garden, 2021, [online], Available (2018): https://www.gardeningknowhow.com.
[96] Robert S. Zeigler, Sally A. Leong, Paul S. Teng (Eds.), Rice blast disease, Int. Rice Res. Inst, 1994.
[97] Rice: fungal diseases: stackburn disease, 2021, [online], Available: https://www.eagri.org.
[98] Charlotte Elliott, Bacterial stripe blight of oats, J. Agric. Res. 35 (9) (1927).
[99] Diagnosing Stripe Blight in Oats, Department of Primary Industries and Regional Development, 2016, [online], Available (2021): https://www.agric.wa.gov.au.
[100] M.C. Rush, F. Lee, Rice sheath blight: A major rice disease, Plant Dis. 67 (7) (1983) 829–832, American Pathology Society.
[101] Ashok Kumar Singh, J.N. Srivastava, Sheath blight disease of paddy and their management, in: Recent Advances in the Diagnosis and Management of Plant Diseases, Springer, New Delhi, 2015, pp. 91–99.
[102] Nagaraju V. Muniyappa, S.J. Singh, K. Virupakshappa, Occurrence of a mosaic virus disease on sunflower in Karnataka, Indian Phytopath. 50 (2) (1997) 277–281.
[103] Mosaic Virus, Planet Natural Research Center, 2021, [online], Available(2021): https://www.planetnatural.com.
[104] Randa Elqassas, Naser Samy S. Abu, Expert system for the diagnosis of mango diseases, Int. J. Acad. Eng. Res. (IJAER) (2000) 10–18, ISSN.
[105] Rust, Planet Natural Research Center, 2021, [online], Available: https://www.planetnatural.com.
[106] M.D. Tausif Mallick, Shrijeet Biswas, Amit Kumar Das, Himadri Nath Saha, Amlan Chakrabarti, Nilanjan Deb, Deep learning based automated disease detection and pest classification in Indian mung bean, Multimedia Tools Appl. 82 (8) (2023) 12017–12041.
[107] Melanie Katawczik, Asimina L. Mila, Plant age and strain of *Ralstonia solanacearum* affect the expression of resistance of tobacco cultivars to Granville wilt, Tob. Sci. (2012) 8–13.
[108] Granville Wilt of Tobacco Tobacco Disease Information, NC State Extension Publications, 2019, [online], Available (2021): https://www.content.ces.ncsu.edu.
[109] Lior Gur, Moshe Reuveni, Yigal Cohen, Occurrence and etiology of Alternaria leaf blotch and fruit spot of apple caused by Alternaria alternata f. sp. mali on cv. Pink lady in Israel, Eur. J. Plant Pathol. 147 (3) (2017) 695–708.
[110] Jan W. Henfling, Late Blight of Potato, International Potato Center, 1987.

[111] Late blight of potato and tomato: declared pest, 2019, [online], Available (2021): https://www.indianexpress.com.
[112] Hannah Jones, John M. Whipps, Sarah Jane Gurr, The tomato powdery mildew fungus *Oidium neolycopersici*, Mol. Plant Path. 2 (6) (2001) 303–309.
[113] Linda Hagen, A.J. Cespedes, How to get rid of powdery mildew, 2021, Garden Design, [online], Available: https://www.gardendesign.com.
[114] Reni Chaerani, Roeland E. Voorrips, Tomato early blight (*Alternaria solani*): the pathogen, genetics, and breeding for resistance, J. Gen. Plant Pathol. 72 (6) (2006) 335–347.
[115] Early Blight of Tomato, University of Mannesota Extension, 2018, [online], Available (2021): https://extension.umn.edu/diseases/early-blight-tomato.
[116] C.H. Bock, P.E. Parker, A.Z. Cook, T.R. Gottwald, Visual rating and the use of image analysis for assessing different symptoms of citrus canker on grapefruit leaves, Plant Dis. 92 (4) (2008) 530–541.
[117] Citrus Canker, Department of Primary Industries and Regional Development, 2019, [online], Available (2021): https://www.agric.wa.gov.au.
[118] K. Gopal, Lakshmi L. Mukunda, G. Sarada, T. Nagalakshmi, Sankar T. Gouri, V. Gopi, K.T.V. Ramana, Citrus melanose (Diaporthecitri wolf): a review, Int. J. Curr. Microbiol. Appl. Sci. 3 (4) (2014) 113–124.
[119] Citrus Diseases Melanose, University Florida, 2021, [online], Available https://www.idtools.org.
[120] Eldon I. Zehr, Control of brown rot in peach orchards, Plant Dis. 66 (12) (1982) 1101–1105.
[121] Norman Latancette, Brown rot management in a wet growing season: Part I, 2015, [online], Available(2021): https://www.plant-pest-advisory.rutgers.edu.
[122] Kenton E. Dashiell, C.N. Akem, Yield losses in soybeans from frogeye leaf spot caused by Cercosporasojina, Crop Protection 10 (6) (1991) 465–468.
[123] Frogeye leaf spot, 2021, [online], Available: https://www.m.farms.com.
[124] Pati Pratap Kumar, Monica Sharma, Raj Kumar Salar, Ashutosh Sharma, A.P. Gupta, B. Singh, Studies on leaf spot disease of withaniasomnifera and its impact on secondary metabolites, Indian J. Microbiol. 48 (4) (2008) 432–437.
[125] Johnny Morgan, Leaf Spot Disease Appearing on Indian Hawthorn, LSU College of Agriculture, 2019, [online], Available (2021): https://www.lsuagcenter.com.
[126] Ann Brooks Gould, James H. Lashomb, Bacterial Leaf Scorch of ShadeTrees, American Pathological Society, 2021, [online], Available: https://www.apsnet.org.
[127] Steven A. Brooks, Merle M. Anders, Kathleen M. Yeater, Effect of cultural management practices on the severity of false smut and kernel smut of rice, Plant Dis. 93 (11) (2009) 1202–1208.
[128] Smutplant disease, 2021, The Editors of Encyclopaedia Britannica, [online], Available: https://www.britannica.com.
[129] "Smut plant disease.(Smut plant (2021))" The Editors of Encyclopaedia Britannica, [online], Available (2021):https://www.britannica.com.
[130] Philippe Rott, Michael J. Davis, Leaf scald, in: A Guide to Sugarcane Diseases, Vol. 38, 2000, p. 44.
[131] D. Ganguly, Studies on the stackburn disease of rice and identity of the causal organism, J. Ind. Bot. Soc. 26 (4) (1947).
[132] T.T. Tsay, Y.H. Cheng, Y.C. Teng, M.D. Lee, W.S. Wu, Y.Y. Lin, Bionomics and control of rice white tip disease nematode, *Aphelenchoides besseyi*, Plant Prot. Bull. (Taipei) 40 (3) (1998) 277–286.
[133] Groth Donald, White Tip Nematode Damage, LSU College of Agriculture, 2011, [online], Available (2021): http://www.lsuagcenter.com.
[134] O.M. Olanya, Campbell C. Lee, Analysis of epidemics of Leptosphaerulina leaf spots on alfalfa and white clover in time and space, Phytopathology 80 (12) (1990) 1341–1347.
[135] Leaf Symptoms of Leptosphaerulina Leaf Spot, Iwoa University, 2021, [online], Available: https://www.ent.iastate.edu.
[136] Pierce Newton Barris, Peach Leaf Curl: Its Nature and Treatment, No. 20, US Government Printing Office, 1900.
[137] Bill Shane, Peach leaf curl is one scary disease, 2018, [online], Available(2021): https://www.growingproduce.com.
[138] Joël L. Vanneste (Ed.), Fire Blight: the Disease and Its Causative Agent, *Erwinia amylovora*, CABI, 2000.
[139] Fireblight: Symptoms, Causes and Treatment, University of Georgia, 2014, [online], Available (2021).
[140] R.M. Beresford, D.W.L. Manktelow, Economics of reducing fungicide use by weather-based disease forecasts for control of *Venturia inaequalis* in apples, N. Z. J. Crop Hortic. Sci. 22 (2) (1994) 113–120.
[141] Phaethon, What Is Fire Blight?, Hudson Trees Service, 2020, [online], Available (2021): https://www.connect2local.com.
[142] Stanisław Kalisz, Jan Oszmiański, Aneta Wojdyło, Increased content of phenolic compounds in pear leaves after infection by the pear rust pathogen, Physiol. Mol. Plant Path. 91 (2015) 113–119.
[143] Nichole Gauthier, Apple scab, Plant Health Instr. 2018 (2021) [online], Available: https://www.apsnet.org.
[144] Carlos Casela, Bobby Renfro, Anatole F. Krattiger, Diagnosing Maize Diseases in Latin America, No. 633.15 D536, International Service for the Acquisition of Agri-Biotech Applications, Ithaca, NY (EUA), 1998.
[145] Kazakov Maksim, Garden diseases - Pear rust, 2021, [online], Available: https://www.thompson-morgan.com.
[146] R.L. Schlub, L.J. Smith, L.E. Datnoff, K. Pernezny, An overview of target spot of tomato caused by *Corynespora cassiicola*, in: II International Symposium on Tomato Diseases, Vol. 808, 2007, pp. 25–28.
[147] Tomato diseases: TARGET SPOT, 2021, [online], Available: https://www.plantpath.ifas.ufl.edu.
[148] Bob Harveson, Cowpea Bacterial Wilt-an Old Disease in a New Crop, Vol. 9, Institute of Agriculture and Natural Resources, 2018, [online], Available (2021): https://www.cropwatch.unl.edu.
[149] Caitilyn Allen, Philippe Prior, A.C. Hayward, Bacterial Wilt Disease and the Ralstonia Solanacearum Species Complex, American Phytopathological Society (APS Press), 2005.
[150] R. Ganesh Babu, C. Chellaswamy, Different stages of disease detection in squash plant based on machine learning, J. Biosci. 47 (1) (2022) 1–14.
[151] M.A. Stahmann, B.G. Clare, W. Woodbury, Increased disease resistance and enzyme activity induced by ethylene and ethylene production of black rot infected sweet potato tissue, Plant Physiol. 41 (9) (1966) 1505–1512.
[152] Black rot, 2020, Infonetbipovision [online], Available (2021): https://www.infonet-biovision.org.
[153] Julian M.J. Ward, Erik L. Stromberg, David C. Nowell, W. Nutter Forrest Jr., Gray leaf spot: a disease of global importance in maize production, Plant Dis. 83 (10) (1999) 884–895.
[154] D. Muller, Northern Corn Leaf Blight of Corn, Crop Protection Network, 2021, [online], Available : https://www.cropprotectionnetwork.org.
[155] Daren Mueller, Grayleafspot (Cercosporazeae-maydis), 2012, [online], Available (2021): http://www.forestryimages.org/browse/detail.cfm?imgnum=546507.
[156] P.R. Scott, T.W. Hollins, Effects of eyespot on the yield of winter wheat, Ann. Appl. Biol. 78 (3) (1974) 269–279.
[157] A. Sisson, D. Mueller, A. Robertson, Eyespot of corn, 2021, Crop Protection Network A Product of Land Grant Universities, [online], Available: https://www.cropprotectionnetwork.org.
[158] Jean Carlier, Marie-Françoise Zapater, Fabienne Lapeyre, David R. Jones, Xavier Mourichon, Septoria leaf spot of banana: a newly discovered disease caused by *Mycosphaerell aeumusae* (anamorph *Septoria eumusae*), Phytopathology 90 (8) (2000) 884–890.
[159] Marcia P. McMullen, Tika B. Adhikari, Bacterial Leaf Streak and Black Chaff of Wheat, NDSU Extension Service, North Dakota State University, 2011.
[160] Stphen Wegulo, Wheat disease update: Bacterial streak and black chaff, 2019, [online], Available (2021): https://www.cropwatch.unl.edu.
[161] L. Liu, J.W. Kloepper, S. Tuzun, Induction of systemic resistance in cucumber against bacterial angular leaf spot by plant growth-promoting rhizobacteria, Phytopathology 85 (8) (1995) 843–847.
[162] E. McKenzie, Bean angular leaf spot, 2013, Biosecurity New Zealand, [online], Available (2021): https://www.greenline.co.ke.
[163] Ana Niurka Hernández-Lauzardo, Silvia Bautista-Baños, Miguel Gerardo Velázquez-del Valle, José Luis Trejo-Espino, Identification of *Rhizopus stolonifer* (Ehrenb.: Fr.) Vuill., causal agent of Rhizopus rot disease of fruits and vegetables, Rev. Mex. Fitopatol. 24 (1) (2006) 65–69.
[164] S.H. Ahn, S.J. Lee, K.R. Kim, Studies on the cause and control of sun scald of plum, Korean J. Hortic. Sci. 4 (1970) 87–91.
[165] Anne Baley, What is sunscald: Learn about sunscald on plants, 2018, [online], Available (2021): https://www.gardeningknowhow.com.
[166] Davil L. Roberts, Southwest canker, in: The Plant Doctor's Landscape Tips, 2013, [online]Available (2021): http://www.treedoctor.anr.msu.edu/landscape_tips/Oct13_SouthwestCanker.pdf.
[167] Vianey Marín-Cevada, Jesús Caballero-Mellado, Rocío Bustillos-Cristales, Jesús Muñoz Rojas, Miguel A. Mascarúa-Esparza, Miguel Castañeda Lucio, Lucía López-Reyes, Lourdes Martínez-Aguilar, Luis E. Fuentes-Ramírez, Tatumellaptyseos, an unrevealed causative agent of pink disease in pineapple, J. Phytopath. 158 (2) (2010) 93–99.
[168] Pink disease, 2018, Queensland Government, [online], Available(2021): https://www.business.qld.gov.au.
[169] L.A. Tatum, The southern corn leaf blight epidemic, Science 171 (3976) (1971) 1113–1116, The Plant Science Research Division, Agricultural Research Service, U.S. Department of Agriculture, Beltsville, Maryland 20705.
[170] C. Grau, Southern corn leaf blight of corn, 2021, Crop Protection Network A Product of Land Grant Universities, [online], Available: https://www.cropprotectionnetwork.org.
[171] H.G. Welz, H.H. Geiger, Genes for resistance to northern corn leaf blight in diverse maize populations, Plant Breeding 119 (1) (2000) 1–14.
[172] Fu-hua Li, Z. Ye, Yu-tao Wang, Mian-ping Xiong, The research progress of maize Curvularia leaf spot disease, J. Maize Sci. 12 (2) (2004) 97–101.

[173] Kiersten Wise, Nolan Anderson, Kelsey Mehl, Carl A. Bradley, Curvularia Leaf Spot, College of Agriculture, Food and Environment Cooperative Extension Service, 2019, [online], Available (2021): https://www.plantpathology.ca.uky.edu.
[174] Jing Li, Ji-hang Cheng, Jing-yuan Shi, Fei Huang, Brief introduction of back propagation (BP) neural network algorithm and its improvement, in: Advances in Computer Science and Information Engineering, Springer, Berlin, Heidelberg, 2012, pp. 553–558.
[175] Yoshimi Okada, Cucumber green mottle mosaic virus, in: The Plant Viruses, Springer, Boston, MA, 1986, pp. 267–281.
[176] Cucumber Green Mosaic Virus, American seed trade association, 2018, [online], Available (2021): https://www.betterseed.org.
[177] T.A. Melton, Control of Tobacco Mosaic Virus on Flue-Cured Tobacco, North Carolina Cooperative Extension Service, 2009, [online], Available (2021).
[178] Elise L. Dekker, Antonius F.L.M. Derks, Cees J. Asjes, Miriam E.C. Lemmers, John F. Bol, Simon A. Langeveld, Characterization of potyviruses from tulip and lily which cause flower-breaking, J. Gen. Virol. 74 (5) (1993).
[179] Helen M. Rothnie, Yvan Chapdelaine, Thomas Hohn, Pararetroviruses and retroviruses: a comparative review of viral structure and gene expression strategies, in: Advances in Virus Research, Vol. 44, Academic Press, 1994, pp. 1–67.
[180] Emerson Joanne B. BakAurélie, Cauliflower mosaic virus (CaMV) biology, management, and relevance to GM plant detection for sustainable organic agriculture, Front. Sustain. Food Syst. (2020) Mini Review Article, [online], Available (2021): https://www.frontiersin.org.
[181] Symptoms of PVY, 2021, AHDB Potatoes is a division of the Agriculture and Horticulture Development Board (AHDB), [online], Available: https://www.secure.fera.defra.gov.uk.
[182] Francesco Calzarano, Stefano Di Marco, Vincenzo D'agostino, Silvia Schiff, Laura Mugnai, Grapevine leaf stripe disease symptoms (esca complex) are reduced by a nutrients and seaweed mixture, Phytopathol. Mediterr. (2014) 543–558.
[183] Esca, 2021, [online], Available: https://www.plantix.net.
[184] Misbakhul Munir, B. Amsden, E. Dixon, L. Vaillancourt, N.A. Ward Gauthier, Characterization of colletotrichum species causing bitter rot of apple in Kentucky orchards, Plant Dis. 100 (11) (2016) 2194–2203.
[185] Bitter rot, 2021, [online], Available: https://www.barmac.com.au.
[186] Sarah J. Pethybridge, Bryan J. Brown, Julie R. Kikkert, Matthew R. Ryan, Rolled–crimped cereal rye residue suppresses white mold in no-till soybean and dry bean, Renew. Agric. Food Syst. 35 (6) (2020) 599–607.
[187] Sclerotinia sclerotiorum-Cottony rot, 2021, [online], Available: https://www.nexles.com.
[188] Y. Petersen, E.L. Mansvelt, E. Venter, W.E. Langenhoven, Detection of Xanthomonas axonopodispv. punicae causing bacterial blight on pomegranate in South Africa, Australas. Plant Pathol. 39 (6) (2010) 544–546.
[189] B.V. Thirumalesh, B. Thippeswamy, M. Krishnappa, In vitro evaluation of chemical formulates on Xanthomonas axonopodispv. punicae, Int. J. Curr. Microbiol. Appl. Sci. 5 (2016) 443–448, [online], Available (2021): https://www.ijemas.com.
[190] Grahame Jackson, Early and late leaf spot of groundnut, 2015, [online], Available (2021): https://www.africasoilhealth.cabi.org.
[191] Snigel Cattlin, Early leaf spot on peanut leaf, 2021, [online], Available: https://www.sciencesource.com.
[192] Groundnut: Minor disease: Leaf spot, 2021, [online], Available: https://www.eagri.org.
[193] P. Subrahmanyam, D. McDonald, Rust disease of groundnut, 13, 1983.
[194] Groundnut: Major disease: Rust, 2021, [online], Available: https://www.eagri.org.
[195] D.V.R. Reddy, A. S. Ratna, M.R. Sudarshana, F. Poul, Kumar I. Kiran, Serological relationships and purification of bud necrosis virus, a tospovirus occurring in peanut (*Arachis hypogaea* l.) in India, Ann. Appl. Biol. 120 (2) (1992) 279–286.
[196] P. Subrahmanyam, S. Wongkaew, D.V.R. Reddy, James W. Demski, D. McDonald, S.B. Sharma, D.H. Smith, Field Diagnosis of Groundnut Diseases, International Crops Research Institute forthe Semi-Arid Tropics, 1992.
[197] Steven T. Koike, Diana M. Henderson, Edward E. Butler, Leaf spot disease of spinach in California caused by *Stemphylium botryosum*, Plant Dis. 85 (2) (2001) 126–130.
[198] Mike Derie, Spinach-Stemphylium, Washington State University Extension, 2021, [online], Available: https://www.mtvernon.wsu.edu.
[199] Laércio Zambolim, Current status and management of coffee leaf rust in Brazil, Trop. Plant Pathol. 41 (1) (2016) 1–8, Departamento de Fitopatologia, Universidade Federal de Viçosa, Viçosa, MG, 36570-900, Brazil.
[200] Coffee Leaf Rust, World Coffee Research Purdue University, 2021, [online], Available, https://www.worldcoffeeresearch.org.
[201] J.M. Waller, P.D. Bridge, R. Black, G. Hakiza, Characterization of the coffee berry disease pathogen, *Colletotrichum kahawae* sp. nov, Mycol. Res. 97 (8) (1993) 989–994.
[202] M.C. Silva, V.M.P. Várzea, Coffee berry disease, 2006, [online], Available (2021): https://www.padil.gov.au.
[203] Julie Flood (Ed.), Coffee Wilt Disease, CABI, 2010.
[204] Coffee wilt disease, 2021, [online], Available: https://www.hawaiicoffeed.com.
[205] Nichlas J. Brazee, Cedar-Apple Rust, The Center for Agriculture, Food and the Environment, 2020, [online], Available (2021): https://www.ag.umass.edu.
[206] Ground Ivy and Orange Growths on Cedar Trees, University of Connecticut Home and garden Education Center, 2010, [online], Available (2021): http://uconnladybug.wordpress.com/2010/04/30/ground-ivy-and-orange-growths-on-cedar-trees/.
[207] Lisa Emele Hoffman, Wayne F. Wilcox, Utilizing epidemiological investigations to optimize management of grape black rot, Phytopathology 92 (6) (2002) 676–680.
[208] Nivedita R. Kakade, Dnyaneswar D. Ahire, Real time grape leaf disease detection, Int. J. Adv. Res. Innov. Ideas Educ. (IJARIIE) 1 (04) (2015) 1.
[209] Mummies Black, Black rot of grape, 2020, https://www.evineyardapp.com/. (Accessed November 2020).
[210] Diagnosing Barley Scald, Department of Primary Industries and Regional Development, 2015, [online], Available (2021): https://www.agric.wa.gov.au.
[211] Tan spot, 2021, Available at: https://cropscience.bayer.co.uk/threats/diseases/cereal-diseases/tan-spot/. (Accessed June 2021).
[212] Peacock spot, 2021, Available at: http://www.australisplants.com.au/olives/peacock.htm/. (Accessed June 2021).
[213] Cannabis aphids, 2021, Available at: https://www.koppert.com/challenges/aphids/cannabis-aphid/. (Accessed June 2021).
[214] Grape mites, 2021, Available at: https://www.syngenta.com.au/news/vineyard/lets-talk-mites/. (Accessed June 2021).
[215] Grapes: Diseases and symptoms, 2021, [online], Available: https://www.vikaspedia.in.
[216] White fly, 2021, Available at: https://www.growveg.com/guides/5-organic-controls-for-greenhouse-whitefly/. (Accessed June 2021).
[217] Mealybugs, 2021, Available at: https://www.thespruce.com/organic-mealybug-control-1316088. (Accessed June 2021).
[218] Leaf miners, 2021, Available at: https://www.thespruce.com/leafminer-damage-to-plants-leaves-1402698/. (Accessed June 2021).
[219] Scale insects, 2021, Available at: https://www.britannica.com/animal/scale-insect/. (Accessed June 2021).
[220] Citrus leaf miner, 2021, Available at: https://www.cultifort.com/en/citrus-leaf-miner-phyllocnistis-citrella/. (Accessed June 2021).
[221] White tininess, Available at: https://www.thegreenpinky.com/white-spots-basil-plants/Accessd%20Feb%202022.
[222] Berry disease, 2022, Available at: https://blogs.cornell.edu/berrytool/strawberries/strawberries-leaf-spot/. (Accessed February 2022).
[223] Quick wilt, 2022, Available at https://vikaspedia.in/agriculture/crop-production/integrated-pest-managment/ipm-for-spice-crops/ipm-strategies-for-black-pepper/black-pepper-diseases-and-symptoms/. (Accessed February 2022).
[224] Quick wilt image, 2022, Available at: http://sumamyu.blogspot.com/2015/09/rice-blast-disease-in-paddy-symt0ms-of.html/. (Accessed Feb 2022).
[225] Foot rot /quick wilt (Quick wilt) Available at: https://vikaspedia.in/agriculture/crop-production/integrated-pest-managment/ipm-for-spice-crops/ipm-strategies-for-black-pepper/black-pepper-diseases-and-symptoms/ Accessed Feb 2022.
[226] Solar scorch, 2022, Available at: https://www.missouribotanicalgarden.org/gardens-gardening/your-garden/help-for-the-home-gardener/advice-tips-resources/pests-and%20problems/environmental/scorch/Accessed%20Feb%202022.
[227] Citrus greening, 2022, Available at: https://cen.acs.org/biological-chemistry/biochemistry/Citrus-greening-killing-worlds-orange/97/i23/Accessed%20Feb%202022.
[228] Red rot, 2022, Available at: https://agritech.tnau.ac.in/crop_protection/sugarcane_diseases/sugarcane_d4/. (Access February 2022).
[229] Bean pod mottle, 2022, Available at: https://www.invasive.org/browse/detail.cfm?imgnum=5581650/. (Access February 2022).
[230] Sugarcane mosaic virus, 2022, Available at: https://pestoscope.com/product/sugarcane-mosaic-virus-scmv//. (Access February 2022).
[231] Brown spot, 2022, Available at: https://www.thespruce.com/treating-brown-spots-on-leaves-5076039/Access.
[232] Sarah D. Williams, Michael J. Boehm, Francesca Peduto Hand, Bacterial Diseases of Plants Agriculture and Natural Resources, CFAES Publication, 2017, https://www.ohioline.osu.edu. (Accessed January 2021).
[233] Roberts, Community of pathogenic plant viruses found in the human gut, PLoSBiol 4 (1) (2006) 0004–0012, http://dx.doi.org/10.1371/journal.pbio.0040015, Accessed January 2021.
[234] Rabbia Mahum, Haris Munir, Zaib-Un-Nisa Mughal, Muhammad Awais, Falak Sher Khan, Muhammad Saqlain, Saipunidzam Mahamad, Iskander Tlili, A novel framework for potato leaf disease detection using an efficient deep learning model, Hum. Ecol. Risk Assess. (2022) 1–24.

[235] Jolene Hansen, How to identify and control common plant fungal diseases, 2021, https://www.gandentech.com. (Accessed January 2021).
[236] Stem-chewing insects, 2021, Available at: https://plantcaretoday.com/caterpillar-control.html. (Accessed June 2021).
[237] Pest, 2021, Available at: https://portal.ct.gov/CAES/Plant-Pest-Handbook/pph-Introductory/Insects-and-their-Injury-to-Plants. (Accessed June 2021).
[238] Spider mite, 2021, Available at https://www.lamtree.com/spider-mites/. (Accessed June 2021).
[239] Root-chewing insect, 2021, Available at: https://fruitgrowersnews.com/news/grape-root-borer-seen-eastern-u-s-vineyards/. (Accessed June 2021).
[240] Sucking insects, 2021, Available at: https://www.britannica.com/animal/aphid. (Accessed June 2021).
[241] S. Veni, An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method, in: 2016 international conference on recent trends in information technology (ICRTIT), IEEE, 2016, pp. 1–6.
[242] Md Sultan Mahmud, Qamar U. Zaman, Travis J. Esau, Young K. Chang, Gordon W. Price, Balakrishnan Prithiviraj, Real-time detection of strawberry powdery mildew disease using a mobile machine vision system, Agronomy 10 (7) (2020) 1027.
[243] Ismail El Massi, Youssef Es-saady, Mostafa El Yassa, Driss Mammass, Abdeslam Benazoun, Automatic recognition of vegetable crops diseases based on neural network classifier, Int. J. Comput. Appl. 158 (4) (2017) 48–51.
[244] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, Darko Stefanovic, Deep neural networks-based recognition of plant diseases by leaf image classification, Comput. Intell. Neurosci. (2016).
[245] Erika Fujita, Yusuke Kawasaki, Hiroyuki Uga, Satoshi Kagiwada, Hitoshi Iyatomi, Basic investigation on a robust and practical plant diagnostic system, in: 2016 15th IEEE International Conference on Machine Learning and Applications, ICMLA, IEEE, 2016, pp. 989–992.
[246] Jihen Amara, Bassem Bouaziz, Alsayed Algergawy, A deep learning-based approach for banana leaf diseases classification, in: Datenbanksystemefür Business, Technologie und Web (BTW 2017)-Workshopband, 2017, pp. 79–88.
[247] Konstantinos P. Ferentinos, Myrto Barda, Dave Damer, An image-based deep learning model for cannabis diseases, nutrient deficiencies and pests identification, in: EPIA Conference on Artificial Intelligence, Springer, Cham, 2019, pp. 134–145.
[248] Sandhya Venu Vasantha, Kiranmai Bejjam, S. Rama Krishna, Techniques for rice leaf disease detection using machine LearningAlgorithms, Int. J. Eng. Res. Technol. 9 (8) (2021) 162–166.
[249] Farhana Sharifah Syed-Ab-Rahman, Hesamian Mohammad Hesam, Prasad Mukesh, Citrus disease detection and classification using end-to-end anchor-based deep learning model, Appl. Intell. 52 (1) (2022) 927–938.
[250] Aditya Khamparia, Gurinder Saini, Deepak Gupta, Ashish Khanna, Shrasti Tiwari, C. de Albuquerque Victor Hugo, Seasonal crops disease prediction and classification using deep convolutional encoder network, 39 (2) (2020) 818–836.
[251] Lakshay Goyal, Chandra Mani Sharma, Anupam Singh, Pradeep Kumar Singh, Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture, Inform. Med. Unlocked (2021) 100642.
[252] Sinan Uğuz, Nese Uysal, Classification of olive leaf diseases using deep convolutional neural networks, Neural Comput. Appl. 33 (9) (2021) 4133–4149.
[253] Kyosuke Yamamoto, Wei Guo, Yosuke Yoshioka, Seishi Ninomiya, On plant detection of intact tomato fruits using image analysis and machine learning methods, Sensors 14 (7) (2014) 12191–12206.
[254] Chebet Too-Edna, Li Yujian, Sam Njuki, Liu Yingchun, A comparative study of fine-tuning deep learning models for plant disease identification, Comput. Electron. Agric. 161 (2019) 272–279.
[255] G. Geetharamani, Arun Pandian, Identification of plant leaf diseases using a nine-layer deep convolutional neural network, Comput. Electr. Eng. 76 (2019) 323–338.
[256] Junde Chen, Defu Zhang, Yaser A. Nanehkaran, Dele Li, Detection of rice plant diseases based on deep transfer learning, J. Sci. Food Agric. 100 (7) (2020) 3246–3256.
[257] Thair A. Salih, Deep learning convolution neural network to detect and classify tomato plant leaf diseases, Open Access Libr. J. 7 (05) (2020) 1.
[258] Suresh Gunasekaran, Kandasamy Gunavathi, Delta tributary network—An efficient alternate approach for bottleneck layers in CNN for plant disease classification, in: IET Image Processing, 2020.
[259] Muhammad E.H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Mohamed Arselene Ayari, Aftab Ullah Khan, Muhammad Salman Khan, Nasser Al-Emadi, Mamun Bin Ibne Reaz, Mohammad Tariqul Islam, Sawal Hamid Md Ali, Automatic and reliable leaf disease detection using deep learning techniques, AgriEngineering 3 (2) (2021) 294–312.
[260] P.E. Rubini, P. Kavitha, Deep learning model for early prediction of plant disease, in: 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks, ICICV, IEEE, 2021, pp. 1104–1107.
[261] Muhammad Azim, Mohammad Khairul Islam Anwarul, Md Marufur Rahman, Farah Jahan, An effective feature extraction method for rice leaf disease classification, Telkomnika 19 (2) (2021) 463–470.
[262] Atila Ümit, Murat Uçar, Kemal Akyol, Emine Uçar, Plant leaf disease classification using efficientnet deep learning model, Ecol. Inform. 61 (2021) 101182.
[263] Balasubramanian VijayaLakshmi, Vasudev Mohan, Kernel-based PSO and FRVM: An automatic plant leaf type detection using texture, shape, and color features, Comput. Electron. Agric. 125 (2016) 99–112.
[264] S. Ashwinkumar, S. Rajagopal, B. Jegajothi, Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks, Mater. Today: Proc. 51 (2022) 480–487.
[265] Sharada P. Mohanty, David P. Hughes, Marcel Salathé, Using deep learning for image-based plant disease detection, Front. Plant Sci. 7 (2016) 1419.
[266] Patrick Mensah Kwabena, Benjamin Asubam Weyori, Ayidzoe Abra Mighty, Gabor capsule network for plant disease detection, Int. J. Adv. Comput. Sci. Appl. 11 (10) (2020).
[267] Amanda Ramcharan, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed, James Legg, David P. Hughes, Deep learning for image-based cassava disease detection, Front. Plant Sci. 8 (2017) 1852.
[268] Kaizhou Li, Jianhui Lin, Jinrong Liu, Yandong Zhao, Using deep learning for image-based different degrees of ginkgo leaf disease classification, Information 11 (2) (2020) 95.
[269] Groundnut: Major disease: Groundnut bud necrosis disease, 2021, [online], Available: https://www.eagri.org.
[270] Ritaban Dutta, Smith Daniel, Yanfeng Shu, Qing Liu, Petra Doust, Shaun Heidrich, Salad leaf disease detection using machine learning based hyper spectral sensing, in: SENSORS, IEEE, 2014, pp. 511–514.
[271] Pierre Barré, Ben C. Stöver, Kai F. Müller, Volker Steinhage, LeafNet: A computer vision system for automatic plant species identification, Ecol. Inform. 40 (2017) 50–56.
[272] Akshay Kumar, M. Vani, Image based tomato leaf disease detection, in: 2019 10th International Conference on Computing, Communication and Networking Technologies, ICCCNT, IEEE, 2019, pp. 1–6.
[273] Vishwanath R Udupi, Identification of soybean diseases using learning vector quantization neural network algorithm, J. Anal. Comput. (2019) 1–7.
[274] A.I. De Castro, R. Ehsani, R. Ploetz, J.H. Crane, J. Abdulridha, Optimum spectral and geometric parameters for early detection of laurel wilt disease in avocado, Remote Sens. Environ. 171 (2015) 33–44.
[275] Lin Yuan, Jing-Cheng Zhang, Ke Wang, Rebecca-W. Loraamm, Wen-Jiang Huang, Ji-Hua Wang, Jin-Ling Zhao, Analysis of spectral difference between the foreside and backside of leaves in yellow rust disease detection for winter wheat, Precis. Agric. 14 (5) (2013) 495–511.
[276] A.H. Kulkarni, H.M. Rai, K.A. Jahagirdar, P.S. Upparamani, A leaf recognition technique for plant classification using RBPNN and Zernike moments, Int. J. Adv. Res. Comput. Commun. Eng. 2 (1) (2013) 984–988.
[277] Adams Begue, Venitha Kowlessur, Upasana Singh, Automatic recognition of medicinal plants using machine learning techniques, Int. J. Adv. Comput. Sci. Appl. 8 (4) (2017) 166–175.
[278] Md Tarek Habib, Md Jueal Mia, Mohammad Shorif Uddin, Farruk Ahmed, An in-depth exploration of automated jackfruit disease recognition, J. King Saud Univ.-Comput. Inf. Sci. (2020).
[279] Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, James Lwasa, Automated vision-based diagnosis of banana bacterial wilt disease and black sigatoka disease, in: International Conference on the Use of Mobile ICT in Africa, 2014, pp. 1–5.
[280] Jaafar Abdulridha, Ozgur Batuman, Yiannis Ampatzidis, UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning, Remote Sens. 11 (11) (2019) 1373.
[281] Mehmet Metin Ozguven, Kemal Adem, Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms, Physica A 535 (2019) 122537.
[282] Jia-Rong Xiao, Pei-Che Chung, Hung-Yi Wu, Quoc-Hung Phan, Jer-Liang Andrew Yeh, Max Ti-Kuang Hou, Detection of strawberry diseases using a convolutional neural network, Plants 10 (1) (2021) 31.
[283] Maheswari Prabhakar, Raja Purushothaman, Durga Prasad Awasthi, Deep learning based assessment of disease severity for early blight in tomato crop, Multimedia Tools Appl. 79 (39) (2020) 28773–28784.
[284] Christoph Römer, Kathrin Bürling, Mauricio Hunsche, Till Rumpf, Georg Noga, Lutz Plümer, Robust fitting of fluorescence spectra for pre-symptomatic wheat leaf rust detection with support vector machines, Comput. Electron. Agric. 79 (2) (2011) 180–188.
[285] H. Muhammad Asraf, M.T. Nooritawati, Rizam M.S.B. Shah, A comparative study in kernel-based support vector machine of oil palm leaves nutrient disease, Procedia Eng. 41 (2012) 1353–1359.

[286] Hui Xu, Fang Lv, Xian Mei Yue, Discussion on sunflower leaf disease diagnosis based on imaging identification, in: Applied Mechanics and Materials, Vol. 577, Trans Tech Publications Ltd, 2014, pp. 1202–1206.
[287] Noura A. Semary, Alaa Tharwat, Esraa Elhariri, Aboul Ella Hassanien, Fruit-based tomato grading system using features fusion and support vector machine, in: Intelligent Systems' 2014, Springer, Cham, 2015, pp. 401–410.
[288] Zhi-Hua Zhou, Jianxin Wu, Wei Tang, Ensembling neural networks: many could be better than all, Artificial Intelligence 137 (1–2) (2002) 239–263.
[289] H. Sabrol, K. Satish, Tomato plant disease classification in digital images using classification tree, in: 2016 International Conference on Communication and Signal Processing, ICCSP, IEEE, 2016, pp. 1242–1246.
[290] Mukesh Kumar Tripathi, Dhananjay D. Maktedar, Recent machine learning based approaches for disease detection and classification of agricultural products, in: 2016 International Conference on Computing Communication Control and Automation, ICCUBEA, IEEE, 2016, pp. 1–6.
[291] V. Pooja, Rahul Das, V. Kanchana, Identification of plant leaf diseases using image processing techniques, in: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development, TIAR, IEEE, 2017, pp. 130–133.
[292] Md Selim Hossain, Mumtahana Mou, Mohammed Mahedi Hasan, Sajib Chakraborty, M. Abdur Razzak, Recognition and detection of tea leaf's diseases using support vector machine, in: 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications, CSPA, IEEE, 2018, pp. 150–154.
[293] Tisen Huang, Rui Yang, Wenshan Huang, Yiqi Huang, Xi Qiao, Detecting sugarcane borer diseases using support vector machine, Inf. Process. Agric. 5 (1) (2018) 74–82.
[294] Yin Min Oo, Nay Chi Htun, Plant leaf disease detection and classification using image processing, Int. J. Res. Eng. 5 (9) (2018) 516–523.
[295] T. Shobana, P. Shanthi, Anand Priya, Glcm Based Plant Leaf Disease Detection Using Multiclass SVM, Int J. Res. Dev. Technol. (2019) 47–51.
[296] Kapil Prashar, Rajneesh Talwar, Chander Kant, Inconsistent cluster analysis with disease feature enhancement (ICADFE) for American cotton leaf disease recognition, in: International Conference on Intelligent Machines Held at Baba Farid College of Engineering and Technology, 2019, pp. 15–16.
[297] Alternaria leaf spot: How to wipe out this fungal foe for good, 2019, [online], Available (2021): https://www.epicgardening.com.
[298] Ting-tiao Pan, Erkinbaev Chyngyz, Da-Wen Sun, Jitendra Paliwal, Hongbin Pu, Pathogenetic process monitoring and early detection of pear black spot disease caused by Alternaria alternata using hyperspectral imaging, Postharvest Biol. Technol. 154 (2019) 96–104.
[299] Feng Jiang, Yang Lu, Yu Chen, Di Cai, Gongfa Li, Image recognition of four rice leaf diseases based on deep learning and support vector machine, Comput. Electron. Agric. 179 (2020) 105824.
[300] Vimal K. Shrivastava, Monoj K. Pradhan, Rice plant disease classification using color features: a machine learning paradigm, J. Plant Pathol. 103 (1) (2021) 17–26.
[301] Zhou Rong, Shun'ichi Kaneko, Fumio Tanaka, Miyuki Kayamori, Motoshige Shimizu, Early detection and continuous quantization of plant disease using template matching and support vector machine algorithms, in: 2013 First International Symposium on Computing and Networking, IEEE, 2013, pp. 300–304.
[302] K. Srunitha, D. Bharathi, Mango leaf unhealthy region detection and classification, in: Computational Vision and Bio Inspired Computing, No. 28, Springer, Cham, 2018, pp. 422–436.
[303] Muhammad Attique Khan, Tallha Akram, Muhammad Sharif, Muhammad Awais, Kashif Javed, Hashim Ali, Tanzila Saba, CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features, Comput. Electron. Agric. 155 (2018) 220–236.
[304] Neha Goyal, Kapil Gupta, Nitin Kumar, Multiclass twin support vector machine for plant species identification, Multimedia Tools Appl. 78 (19) (2019) 27785–27808.
[305] A.-K. Mahlein, T. Rumpf, P. Welke, H.-W. Dehne, L. Plümer, U. Steiner, E.-C. Oerke, Development of spectral indices for detecting and identifying plant diseases, Remote Sens. Environ. 128 (2013) 21–30.
[306] Jun Qin, Biao Wang, Yanlan Wu, Qi Lu, Haochen Zhu, Identifying pine wood nematode disease using UAV images and deep learning algorithms, Remote Sens. 13 (2) (2021) 162.
[307] Faye Mohameth, Bingcai Chen, Sada Kane Amath, Plant disease detection with deep learning and feature extraction using plant village, J. Comput. Commun. 8 (6) (2020) 10–22.
[308] Malusi Sibiya, Mbuyu Sumbwanyambe, Automatic fuzzy logic-based maize common rust disease severity predictions with thresholding and deep learning, Pathogens 10 (2) (2021) 131.
[309] Juan Gómez-Sanchis, José D. Martín-Guerrero, Emilio Soria-Olivas, Martínez-Sober Marcelino, Magdalena-Benedito Rafael, Blasco José, Detecting rottenness caused by penicillium genus fungi in citrus fruits using machine learning techniques, Expert Syst. Appl. 39 (1) (2012) 780–785.
[310] Ahmed R. Luaibi, Tariq M. Salman, Detection of citrus leaf diseases using a deep learning technique, Int. J. Electr. Comput. Eng. 11 (2) (2021) 1719.
[311] Bin Liu, Yun Zhang, DongJian He, Yuxiang Li, Identification of apple leaf diseases based on deep convolutional neural networks, Symmetry 10 (1) (2018) 11.
[312] Yashwant Kurmi, Suchi Gangwar, Dheeraj Agrawal, Satrughan Kumar, Hari Shanker Srivastava, Leaf image analysis-based crop diseases classification, Signal Image Video Process. 15 (3) (2021) 589–597.
[313] José G.M. Esgario, Pedro B.C. de Castro, Lucas M. Tassis, Renato A. Krohling, An app to assist farmers in the identification of diseases and pests of coffee leaves using deep learning, Inf. Process. Agric. 9 (1) (2022) 38–47.
[314] Abrham Debasu Mengistu, Dagnachew Melesew Alemayehu, Seffi Gebeyehu Mengistu, Ethiopian coffee plant diseases recognition based on imaging and machine learning techniques, Int. J. Database Theory Appl. 9 (4) (2016) 79–88.
[315] Zhiyu Liu, Lin Zhu, Xiao-Ping Zhang, Xiaobo Zhou, Li Shang, Zhi-Kai Huang, Yong Gan, Hybrid deep learning for plant leaves classification, in: International Conference on Intelligent Computing, Springer, Cham, 2015, pp. 115–123.
[316] Md Sultan Mahmud, Young K. Chang, Qamar U. Zaman, Travis J. Esau, Detection of strawberry powdery mildew disease in leaf using image texture and supervised classifiers, in: Proceedings of the CSBE/SCGAB 2018 Annual Conference, Guelph, ON, USA, 2018, pp. 22–25.
[317] Parul Sharma, Yash Paul Singh Berwal, Wiqas Ghai, Performance analysis of deep learning CNN models for disease detection in plants using image segmentation, Inf. Process. Agric. 7 (4) (2020) 566–574.
[318] Xiaoyue Xie, Yuan Ma, Bin Liu, Jinrong He, Shuqin Li, Hongyan Wang, A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks, Front. Plant Sci. 11 (2020).
[319] Feng Qin, Liu Dongxia, Sun Bingda, Liu Ruan, Identification of alfalfa leaf diseases using image recognition technology, PLoS One 11 (12) (2016) 1–26.
[320] Alvaro Fuentes, Yoon Sook, Sang Cheol Kim, Dong Sun Park, A robust deep-learning-based detector for real-time tomato plant diseases and pest's recognition, Sensors 17 (9) (2017) 2022.
[321] Jiang Lu, Jie Hu, Guannan Zhao, Fenghua Mei, Changshui Zhang, An in-field automatic wheat disease diagnosis system, Comput. Electron. Agric. 142 (2017) 369–379.
[322] Xihai Zhang, Yue Qiao, Fanfeng Meng, Chengguo Fan, Mingming Zhang, Identification of maize leaf diseases using improved deep convolutional neural networks, IEEE Access 6 (2018) 30370–30377.
[323] Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang, Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks, IEEE Access 7 (2019) 59069–59080.
[324] Everton Castelão Tetila, Bruno Brandoli Machado, Gabriel Kirsten Menezes, Adair da Silva Oliveira, Marco Alvarez, Willian Paraguassu Amorim, Nícolas Alessandro De Souza Belete, Gercina Gonçalves Da Silva, Hemerson Pistori, Automatic recognition of soybean leaf diseases using UAV images and deep convolutional neural networks, IEEE Geosci. Remote Sens. Lett. 17 (5) (2019) 903–907.
[325] Shekofa Ghoury, Cemil Sungur, Akif Durdu, Real-time diseases detection of grape and grape leaves using faster R-CNN and SSD MobileNet architectures, in: International Conference on Advanced Technologies, Computer Engineering and Science, ICATCES 2019, 2019.
[326] Ahmed Afifi, Alhumam Abdulaziz, Abdelwahab Amira, Convolutional neural network for automatic identification of plant diseases with limited data, Plants 10 (1) (2021) 28.
[327] Hesham Tarek, Aly Hesham, Eisa Saleh, Abul-Soud Mohamed, Optimized deep learning algorithms for tomato leaf disease detection with hardware deployment, Electronics 11 (1) (2022) 140.
[328] Heba Kurdi, Amal Al-Aldawsari, Isra Al-Turaiki, Abdulrahman S. Aldawood, Early detection of red palm weevil, *Rhynchophorus ferrugineus* (Olivier), infestation using data mining, Plants 10 (1) (2021) 95.
[329] Rakesh Chandra Joshi, Manoj Kaushik, Malay Kishore Dutta, Srivastava Ashish, Nandlal Choudhary, VirLeafNet: automatic analysis and viral disease diagnosis using deep-learning in vigna mungo plant, Ecol. Inform. 61 (2021) 101197.
[330] Late leafspot a problem in peanuts, 2014, [online], Available (2021): https://www.seminolecropnews.wordpress.com.
[331] Syed Mohammad Minhaz Hossain, Kaushik Deb, Pranab Kumar Dhar, Takeshi Koshiba, Plant leaf disease recognition using depth-wise separable convolution-based models, Symmetry 13 (3) (2021) 511.
[332] Foliage dataset, 2007, Available at: http://www.leafnet.pbarre.de/. Accessed April 2021.
[333] Flavia dataset, 2009, Available at: http://flavia.sourceforge.net/. (Accessed April 2021).
[334] Vijai Singh, Sharma Namita, Singh Shikha, A review of imaging techniques for plant disease detection, Artif. Intell. Agric. (2020).

[335] Apple leaf dataset, 2013, Available at: https://www.quantitative-plant.org/dataset/apple-leaf-dataset/. (Accessed April 2021).
[336] LeafSnap dataset, 2014, Available at, http://leafsnap.com/dataset/. (Accessed April 2021).
[337] Rice leaf disease dataset, 2017, Available at: https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases/. (Accessed April 2021).
[338] Rice diseases dataset, 2022, Available at: https://github.com/aldrin233/RiceDiseases-DataSet.git/. (Accessed 2022).
[339] Plant pathology, 2020, Available at: https://data.mendeley.com/datasets/hb74ynkjcn/4/. (Accessed April 2021).
[340] Plantvillage dataset, 2019, Available at: https://data.mendeley.com/datasets/tywbtsjrjv/1. (Accessed February 2021).
[341] Plant disease dataset, 2021, Available at: https://www.digipathos-rep.cnptia.embrapa.br/. (Accessed April 2021).
[342] New Plant Diseases Dataset, Flowers Recognition and Weed Detection in Soybean Crops datasets are Available at: https://www.kaggle.com/datasets/Accessed%20February%202022.
[343] Plant Seedings Dataset, Available: https://www.kaggle.com/datasets/Accessed%20Feb%202022.
[344] Puneet Mishra, Jean Michel Roger, Douglas N. Rutledge, Ernst Woltering, SPORT pre-processing can improve near-infrared quality prediction models for fresh fruits and agro-materials, Postharvest Biol. Technol. 168 (2020) 111271.
[345] Santi Kumari Behera, Lipsarani Jena, Amiya Kumar Rath, Prabira Kumar Sethy, Disease classification and grading of orange using machine learning and fuzzy logic, in: 2018 International Conference on Communication and Signal Processing, ICCSP, IEEE, 2018, pp. 0678–0682.
[346] Fluor-imagingprinciples.pdf, 2010, Available at: http://www.bu.edu/picf/files/2010/10/.
[347] Fluorescence imaging "Fluor-ImagingPrinciples.pdf", Available at: http://www.bu.edu/picf/files/2010/10/ (2010).
[348] Itzhak Fogel, Sagi Dov, Gabor filters as texture discriminator, Biol. Cybernet. 61 (2) (1989) 103–113.
[349] Irwin Sobel, Gary Feldman, A 3 × 3 isotropic gradient operator for image processing, in: A Talk at the Stanford Artificial Project, 1968, pp. 271–272.
[350] P. Mishra, J.M. Roger, F. Marini, A. Biancolillo, D.N. Rutledge, Parallel pre-processing through orthogonalization (PORTO) and its application to near-infrared spectroscopy, Chemometr. Intell. Lab. Syst. 212 (2021) 104190.
[351] K. Balasamy, S. Suganyadevi, A fuzzy based ROI selection for encryption and watermarking in medical image using DWT and SVD, Multimedia Tools Appl. 80 (5) (2021) 7167–7186.
[352] M. Rajesh Khanna, Data hiding in encrypted images using Arnold transform, in: International Conference on Algorithms, 2017.
[353] Nyma Alamgir, Jong-Myon Kim, Fuzzy clustering based medical image watermarking, in: KIPS Transactions on Software and Data Engineering, Vol. 2, No. 7, 2013, pp. 487–494.
[354] Rafael C. Gonzalez, Richard Eugene Woods, Steven L. Eddins, Digital Image Processing Using MATLAB, Pearson Education India, 2004.
[355] Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, Yi Yang, Random erasing data augmentation, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, No. 07, 2020, pp. 13001–13008.
[356] Alireza Naghizadeh, Dimitris N. Metaxas, Dongfang Liu, Greedy auto-augmentation for n-shot learning using deep neural networks, Neural Netw. 135 (2021) 68–77.
[357] Hongyi Zhang, Moustapha Cisse, Yann N. Dauphin, David Lopez-Paz, mixup: Beyond empirical risk minimization, 2017, arXiv preprint arXiv:1710.09412.
[358] Shunjiro Noguchi, Mizuho Nishio, Masahiro Yakami, Keita Nakagomi, Kaori Togashi, Bone segmentation on whole-body CT using convolutional neural network with novel data augmentation techniques, Comput. Biol. Med. 121 (2020) 103767.
[359] James Pustejovsky, Amber Stubbs, Natural Language Annotation for Machine Learning: A Guide To Corpus-Building for Applications, O'Reilly Media, Inc., 2012.
[360] Sworna Akter, Md Alamgir Hossain, A review on different classification, feature extraction and segmentation methodologies of leaf disease detection using image processing approach, World Acad. Inform. Manag. Sci. 4 (9) (2020) 9434–9440.
[361] James C. Bezdek, Objective function clustering, in: Pattern Recognition with Fuzzy Objective Function Algorithms, Springer, Boston, MA, 1981, pp. 43–93.
[362] Yizong Cheng, Mean shift, mode seeking, and clustering, IEEE Trans. Pattern Anal. Mach. Intell. 17 (8) (1995) 790–799.
[363] Dorin Comaniciu, Peter Meer, Mean shift: A robust approach toward feature space analysis, IEEE Trans. Pattern Anal. Mach. Intell. 24 (5) (2002) 603–619.
[364] Paul S. Bradley, Olvi L. Mangasarian, W. Nick Street, Clustering via concave minimization, in: Advances in Neural Information Processing Systems, 1997, pp. 368–374.
[365] Wei Zhang, DaLing Jiang, The marker-based watershed segmentation algorithm of ore image, in: 2011 IEEE 3rd International Conference on Communication Software and Networks, IEEE, 2011, pp. 472–474.
[366] Radhakrishna Achanta, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, Sabine Süsstrunk, SLIC superpixels compared to state-of-the-art superpixel methods, IEEE Trans. Pattern Anal. Mach. Intell. 34 (11) (2012) 2274–2282.
[367] Geoffrey Holmes, Craig G. Nevill-Manning, Feature selection via the discovery of simple classification rules, 1995, pp. 1–5.
[368] Igor Kononenko, Edvard Šimec, Marko Robnik-Šikonja, Overcoming the myopia of inductive learning algorithms with RELIEFF, Appl. Intell. 7 (1) (1997) 39–55.
[369] Christopher G. Harris, Mike Stephens, A combined corner and edge detector, in: Alvey Vision Conference, No. 15, 1988, pp. 10–5244, 50.
[370] Dong-Chen He, Li Wang, Texture unit, texture spectrum, and texture analysis, IEEE Trans. Geosci. Remote Sens. 28 (4) (1990) 509–512.
[371] Bernhard Schölkopf, Alexander Smola, Klaus-Robert Müller, Nonlinear component analysis as a kernel eigenvalue problem, Neural Comput. 10 (5) (1998) 1299–1319.
[372] Maureen C. Stone, Stone M. C., A survey of color for computer graphics, in: Course at SIGGRAPH, Vol. 744, 2001.
[373] Shen Weizheng, Wu Yachun, Chen Zhanliang, Wei Hongda, Grading method of leaf spot disease based on image processing, in: 2008 International Conference on Computer Science and Software Engineering, No. 6, IEEE, 2008, pp. 491–494.
[374] Jyoti Narwade, Binod Kumar, Local and global color histogram feature for color content-based image retrieval system, in: Proceedings of the International Congress on Information and Communication Technology, Springer, Singapore, 2016, pp. 293–300.
[375] Greg Pass, Zabih Ramin, Justin Miller, Comparing images using color coherence vectors, in: Proceedings of the Fourth ACM International Conference on Multimedia, 1997, pp. 65–73.
[376] Anuradha Badage, Crop disease detection using machine learning: Indian agriculture, Int. Res. J. Eng. Technol. (IRJET) 5 (9) (2018) 866–869.
[377] R. Ramya, P. Kumar, D. Mugilan, M. Babykala, A review of different classification techniques in machine learning using weka for plant disease detection, Int. Res. J. Eng. Technol. (IRJET) 5 (5) (2018) 3818–3823.
[378] Mario Fordellone, Andrea Bellincontro, Fabio Mencarelli, Partial least squares discriminant analysis: A dimensionality reduction method to classify hyperspectral data, 2018, arXiv preprint arXiv:1806.09347.
[379] Umesh Gupta, Deepak Gupta, Mukesh Prasad, Kernel target alignment based fuzzy least square twin bounded support vector mac hine, in: 2018 IEEE Symposium Series on Computational Intelligence, SSCI, IEEE, 2018, pp. 228–235.
[380] Umesh Gupta, Deepak Gupta, Lagrangian twin-bounded support vector machine based on L2-norm, in: Recent Developments in Machine Learning and Data Analytics, Springer, Singapore, 2019, pp. 431–444.
[381] Barenya Bikash Hazarika, Deepak Gupta, Density-weighted support vector machines for binary class imbalance learning, Neural Comput. Appl. 33 (9) (2021) 4243–4261.
[382] Barenya Bikash Hazarika, Deepak Gupta, Density weighted twin support vector machines for binary class imbalance learning, Neural Process. Lett. 54 (2) (2022) 1091–1130.
[383] Alex J. Smola, Bernhard Schölkopf, A tutorial on support vector regression, Stat. Comput. 14 (3) (2004) 199–222.
[384] Deepak Gupta, Umesh Gupta, On robust asymmetric Lagrangian ν-twin support vector regression using pinball loss function, Appl. Soft Comput. 102 (2021) 107099.
[385] Umesh Gupta, Deepak Gupta, An improved regularization based Lagrangian asymmetric ν-twin support vector regression using pinball loss function, Appl. Intell. 49 (10) (2019) 3606–3627.
[386] Umesh Gupta, Deepak Gupta, Least squares large margin distribution machine for regression, Appl. Intell. (2021) 1–36.
[387] Umesh Gupta, Deepak Gupta, On regularization based twin support vector regression with huber loss, Neural Process. Lett. (2021) 1–57.
[388] Tin Kam Ho, Random decision forests, in: Proceedings of 3rd International Conference on Document Analysis and Recognition, No. 1, IEEE, 1995, pp. 278–282.
[389] Leo Breiman, Bagging predictors, Mach. Learn. 24 (2) (1996) 123–140.
[390] Jerome H. Friedman, Forest Baskett, Leonard J. Shustek, An algorithm for finding nearest neighbors, IEEE Trans. Comput. 100 (10) (1975) 1000–1006.
[391] F. Rosenblatt, The perceptron: a probabilistic model for information storage and organization in the brain, Psychol. Rev. 65 (6) (1958) 386.
[392] Martin Schumacher, Reinhard Roßner, Werner Vach, Neural networks and logistic regression: Part i, Comput. Statist. Data Anal. 21 (6) (1996) 661–682.
[393] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representations by error propagation, in: D.E. Rumelhart, J.L. McClelland (Eds.), Parallel Distributed Processing. Exploration in the Microstructure of Cognition, MIT Press, Cambridge, MA, 1986, pp. 318–362.

[394] Backpropagation model, 2022, https://medium.com/analytics-vidhya/multi-layer-perceptron-neural-network-algorithm-and-its-components-d3e997eb42bb/. (Accessed May 2022).
[395] Yann LeCun, D. Touresky, G. Hinton, T. Sejnowski, A theoretical framework for back-propagation, in: Proceedings of the 1988 connectionist models summer school, 1, 1988, pp. 21–28.
[396] Karen Simonyan, Andrew Zisserman, Very deep convolutional networks for large-scale image recognition, 2014, arXiv preprint arXiv:1409.1556.
[397] Teuvo Kohonen, Self-organized formation of topologically correct feature maps, Biol. Cybernet. 43 (1) (1982) 59–69.
[398] Teuvo Kohonen, Learning vector quantization, in: Self-Organizing Maps, Springer Berlin Heidelberg, Berlin, Heidelberg, 1995, pp. 175–189.
[399] Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik, Rich feature hierarchies for accurate object detection and semantic segmentation, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 580–587.
[400] S. Mark, H. Andrew, MobileNetV2: The next generation of on-device computer vision networks, 2018, Google Research.
[401] Mingxing Tan, Quoc Le, Efficientnet: Rethinking model scaling for convolutional neural networks, in: International Conference on Machine Learning, PMLR, 2019, pp. 6105–6114.
[402] Sara Sabour, Nicholas Frosst, Geoffrey E. Hinton, Dynamic routing between capsules, 2017, arXiv preprint arXiv:1710.09829.
[403] Patrick Mensah Kwabena, Benjamin AsubamWeyori, AyidzoeAbra Mighty, Gabor capsule network for plant disease detection, 2017.
[404] Harry Pratt, Bryan Williams, Frans Coenen, Yalin Zheng, Fcnn: Fourier convolutional neural networks, in: Joint European Conference on Machine Learning and Knowledge Discovery in Databases, Springer, Cham, 2017, pp. 786–798.
[405] R. Karthik, M. Hariharan, Sundar Anand, Priyanka Mathikshara, Annie Johnson, R. Menaka, Attention embedded residual CNN for disease detection in tomato leaves, Appl. Soft Comput. 86 (2020) 105933.
[406] Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, Kurt Keutzer, SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5 MB model size, 2016, arXiv preprint arXiv:1602.07360.
[407] Halil Durmuş, Ece Olcay Güneş, Mürvet Kırcı, Disease detection on the leaves of the tomato plants by using deep learning, in: 2017 6th International Conference on Agro-Geoinformatics, IEEE, 2017, pp. 1–5.
[408] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, Zbigniew Wojna, Rethinking the inception architecture for computer vision, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2818–2826.
[409] Thomas G. Dietterich, Ensemble learning, in: The Handbook of Brain Theory and Neural Networks, Vol. 2, 2002, pp. 110–125.
[410] Alex Krizhevsky, Ilya Sutskever, Hinton E. Geoffrey, Imagenet classification with deep convolutional neural networks, Commun. ACM 60 (6) (2017) 84–90.
[411] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Imagenet large scale visual recognition challenge, Int. J. Comput. Vis. 115 (3) (2015) 211–252.
[412] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, Q. Weinberger, Densely connected convolutional networks, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 4700–4708.
[413] Sayed Alireza Sadrossadat, Yazi Cao, Qi-Jun Zhang, Parametric modeling of microwave passive components using sensitivity-analysis-based adjoint neural-network technique, IEEE Trans. Microw. Theory Tech. 61 (5) (2013) 1733–1747.
[414] Mohammad Asif Zaman, Paul C. Hansen, Lars T. Neustock, Punnag Padhy, Lambertus Hesselink, Adjoint method for estimating Jiles–Atherton hysteresis model parameters, J. Appl. Phys. 120 (9) (2016) 093903.