Demilie *Journal of Big Data* (2024) 11:5
https://doi.org/10.1186/s40537-023-00863-9

Journal of Big Data

SURVEY

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Plant disease detection and classification techniques: a comparative study of the performances

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Abstract

One of the essential components of human civilization is agriculture. It helps the economy in addition to supplying food. Plant leaves or crops are vulnerable to different diseases during agricultural cultivation. The diseases halt the growth of their respective species. Early and precise detection and classification of the diseases may reduce the chance of additional damage to the plants. The detection and classification of these diseases have become serious problems. Farmers' typical way of predicting and classifying plant leaf diseases can be boring and erroneous. Problems may arise when attempting to predict the types of diseases manually. The inability to detect and classify plant diseases quickly may result in the destruction of crop plants, resulting in a significant decrease in products. Farmers that use computerized image processing methods in their fields can reduce losses and increase productivity. Numerous techniques have been adopted and applied in the detection and classification of plant diseases based on images of infected leaves or crops. Researchers have made significant progress in the detection and classification of diseases in the past by exploring various techniques. However, improvements are required as a result of reviews, new advancements, and discussions. The use of technology can significantly increase crop production all around the world. Previous research has determined the robustness of deep learning (DL) and machine learning (ML) techniques such as k-means clustering (KMC), naive Bayes (NB), feed-forward neural network (FFNN), support vector machine (SVM), k-nearest neighbor (KNN) classifier, fuzzy logic (FL), genetic algorithm (GA), artificial neural network (ANN), convolutional neural network (CNN), and so on. Here, from the DL and ML techniques that have been included in this particular study, CNNs are often the favored choice for image detection and classification due to their inherent capacity to autonomously acquire pertinent image features and grasp spatial hierarchies. Nevertheless, the selection between conventional ML and DL hinges upon the particular problem, the accessibility of data, and the computational capabilities accessible. Accordingly, in numerous advanced image detection and classification tasks, DL, mainly through CNNs, is preferred when ample data and computational resources are available and show good detection and classification effects on their datasets, but not on other datasets. Finally, in this paper, the author aims to keep future researchers up-to-date with the performances, evaluation metrics, and results of previously used techniques to detect and classify different forms of plant leaf or crop diseases using various image-processing techniques in the artificial intelligence (AI) field.

Keywords: Classification, Detection, DL, Image processing, ML, Plant disease

Introduction

Agricultural biodiversity is essential for providing humans with food and raw materials and is an essential component of human civilization [1, 2]. The disease can occur when pathogenic organisms such as fungi, bacteria, and nematodes; soil PH; temperature extremes; changes in the quantity of moisture and humidity in the air; and other elements continuously harm a plant. Plant diseases can have an impact on the growth, function, and structure of plants and crops, affecting the people that rely on them. The majority of farmers still use manual methods to detect and classify plant ailments because it is difficult to do so early on, and this reduces productivity. Agriculture's productivity is a significant economic factor. As a result, disease identification and classification in plants are critical in agricultural industries [3]. If proper precautions are not taken, it can have serious consequences for plants by reducing the quality, quantity, or productivity of the corresponding products or services. Automatic disease detection and classification recognize symptoms at an early stage, i.e., when they first appear on plant leaves, lowering the amount of labor necessary to monitor large farms of crops.

According to [4] Plant leaf disease is a major issue in rice production, and the disease has the potential to harm the crop, resulting in a drop in products. Farmers have a difficult time detecting and classifying plant leaf diseases. The traditional method of detecting and classifying diseases by physical observation is not always reliable and may result in a significant decrease in agricultural production [5]. Plant diseases attack the leaf initially before infecting the entire plant, reducing production quality and quantity [6]. Recent advances in DL have resulted in numerous approaches for detecting and classifying plant disease using images of infected plants [7]. Early detection and classification of plant diseases is critical for increasing agricultural productivity [8, 9]. Plant diseases reduce crop results by having a negative impact on the crop [10]. Plant disease identification is a major challenge in agriculture for both farmers and experts [11]. Artificial intelligence (AI) increases crop productivity by detecting and classifying plant leaf diseases early on before they spread to other plants on the farm [12]. Accurate plant disease classification would not only increase crop results but will also provide support for various cultivation methods [13]. Every country needs farming to meet its requirements as well as to strengthen its economy. When crop plants are damaged by diseases, the country's production and its economy are also affected [14, 15]. Because of data disparities, selecting an appropriate approach for image processing is always a difficult task.

To produce good results, huge datasets necessitate advanced approaches such as CNN and large image datasets result in increased accuracy rates [16].

Image processing is used to improve the quality of images to extract valuable information from them; as a result of this feature, image processing techniques are used in many areas of the medical and agricultural fields, such as color processing, remote sensing, and pattern recognition. Image processing techniques that are acceptable, effective, and dependable can be used to discover disease in plant leaves. Image processing can be used in a variety of fields, including biology, agriculture, medicine, engineering, computing, etc. Computerized image processing techniques are critical for detecting and classifying plant diseases early before they cause widespread damage to entire crops [17, 18]. To address this, several DL, image processing, and ML techniques were being developed to detect and classify disease in plants using images of plant leaves. DL technologies can help agricultural firms succeed. This research focuses on the comparative study of the performances, evaluation metrics, and results of numerous methodologies and methods previously used to detect and classify different forms of plant leaf diseases using image processing approaches. Accordingly, finding a reliable technique to apply is critical to increasing the yields of agricultural products.

The paper will have the following contributions to the scientific community.

- This paper presents an overview of recent advances in plant disease detection and classification using ML and DL approaches. Accordingly, it provides an in-depth review of the state-of-the-art techniques and methodologies used in the area by covering research published in the field.
- The paper shows how using ML and DL approaches improves the performance and speed of plant disease detection and classification.
- Identifying the best DL technique for multi-class plant disease detection and classification and optimal identification accuracy.
- The development of DL techniques for detecting and classifying numerous plant diseases;
- Addressing the different labeling and class challenges in recognizing plant diseases by recommending multi-class, multi-label DL techniques.
- The use of a new technique with different steps designed to improve plant disease detection and classification in real-world images yields quick results and is suited for real-time applications.

The rest of the paper is organized into different but interrelated subsections. The paper begins by discussing plant disease identification and classification in Sect. "Plant disease identification and classification", factors responsible for plant diseases in Sect. "Factors responsible for plant diseases", detection and classification of plant diseases in Sect. "Detection and classification of plant diseases", plant disease detection and classification techniques in Sect. "Plant disease detection and classification techniques", related works in Sect. "Related works", performance evaluation of plant disease detection and classification in Sect. "Performance evaluation of plant disease detection and classification", results and discussions in Sect. "Results and discussions", and the conclusion and recommendation in Sect. "Conclusion and recommendation".

Plant disease identification and classification

Computer vision is a subdomain of AI that allows machines to counterfeit the human visual system and precisely draw out, inspect, and recognize real-world images in the same way that humans do [19].

ML techniques have been used to detect and classify plant diseases, but with advancements in a subset of ML, DL, this area of research appears to have considerable potential in terms of increasing accuracy. Many developed DL architectures were used, along with various visualization techniques, to detect and classify plant disease symptoms accordingly [20].

Medical diagnosis, espionage, satellite images, and agribusiness are just a few of the rapidly increasing industries that have already shown the benefits of computer vision-based technologies. Computer vision-enabled systems can be used in agriculture to detect and classify plant diseases based on different features or symptoms that have been extracted. It uses a well-defined series of steps beginning with image acquisition and continuing with various image-processing tasks such as scaling, filtering, segmentation, feature extraction, and selection, and finally, detection and classification are performed using ML or DL techniques [21].

Factors responsible for plant diseases

A wide range of agricultural diseases can arise at various stages of plant development and harm the plant's growth, which can have a negative impact on overall crop production [19, 22, 23]. Plant diseases are caused by a variety of conditions at various phases of plant development [24]. As summarized in [22], crop disease-causing variables are categorized into two: biotic factors and abiotic factors. Biotic factors such as viruses, fungi, bacteria, mites, and slugs emerge as a result of microbial infection in plants, whereas abiotic variables such as water, temperature, irradiation, and nutritional deprivation damage plant growth [9, 25–28]. Accordingly, some sample plant leaf images with different diseases from the PlantVillage dataset and different images from other datasets showing healthy and diseased plant leaves have been included in the study [21] and different images from other datasets showing healthy and diseased plant leaves have been summarized in the works of [29] and [30] accordingly. Additionally, the detail computer vision-based techniques and proccsses including field crops, image acquisition, leaf image datasets, image preprocessing (test set, training set, and validation sets), data splitting, and performance assessment methods) for plant disease detection and classification have been clearly indicated in the work of [21]. The details of the factors responsible for plant diseases has been depicted in Fig. 1. Additionally, some sample plant leaf images with different diseases from the PlantVillage dataset and different images from other datasets showing healthy and diseased plant leaves have been depicted in Figs. 2. 3 respectively.

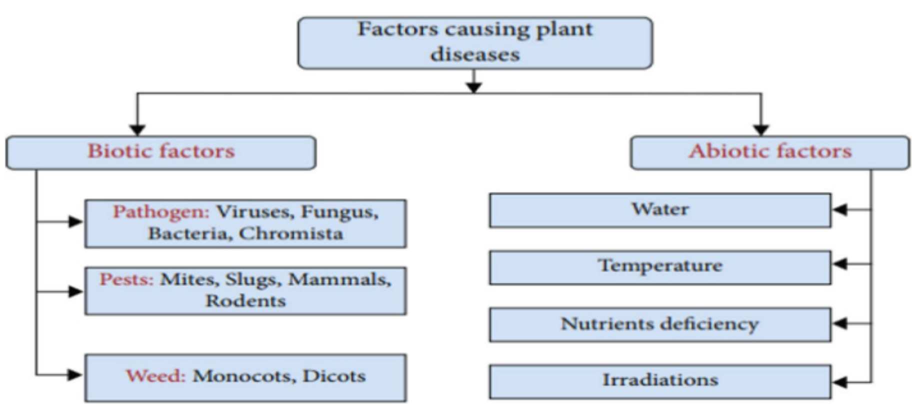

Fig. 1 Factors responsible for plant diseases [22]

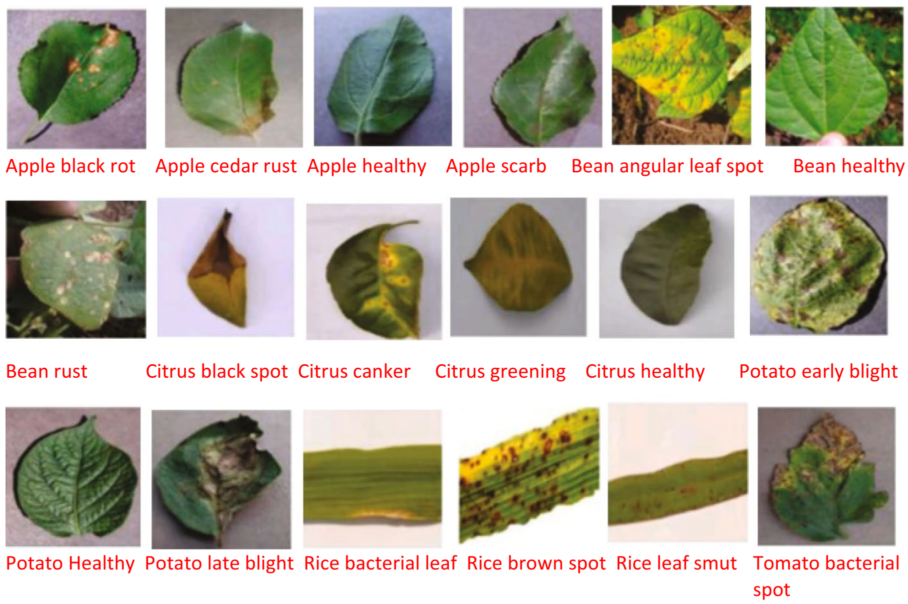

Fig. 2 Some sample plant leaf images with different diseases from the PlantVillage dataset[21]

Some sample plant leaf images with different diseases from the PlantVillage dataset and different images from other datasets showing healthy and diseased plant leaves have been depicted in Figs. 2, 3 respectively.

The detailed computer vision-based techniques for plant disease detection and classification have been depicted in Fig. 4.

Detection and classification of plant diseases

The detection and classification of crop diseases is an essential use of DL, ML, and computer vision techniques in agriculture industries [1]. The aim is to develop algorithms and techniques based on images of leaves or other plant features that can automatically detect and classify agricultural plant diseases. This can help farmers assist and manage the disease. Following a detailed and critical study of numerous recent ML and DL-based approaches developed for plant disease detection and classification in the literature, the author has summarised a few key challenges in crop disease detection and classification, allowing the research community to investigate the causes that may have a significant impact on real-time-based systems for plant identification and diagnosis. Some factors and issues may have an impact on disease identification and classification; the majority of them have been summarised in the studies of [19, 27, 28, 31–38].

Plant disease detection and classification techniques

Machine learning (ML) techniques or algorithms

A. The NB Technique It is a probabilistic classifier variation built on the NB classifier idea [19, 21]. It is assumed that the patterns' prior probabilities are known to exist and that the class labels are assigned their posterior probabilities. In light of this premise, the maximum likelihood values of the data that belong to a specific class label are computed using the posterior probability. It is calculated by applying Baye's theorem to the product

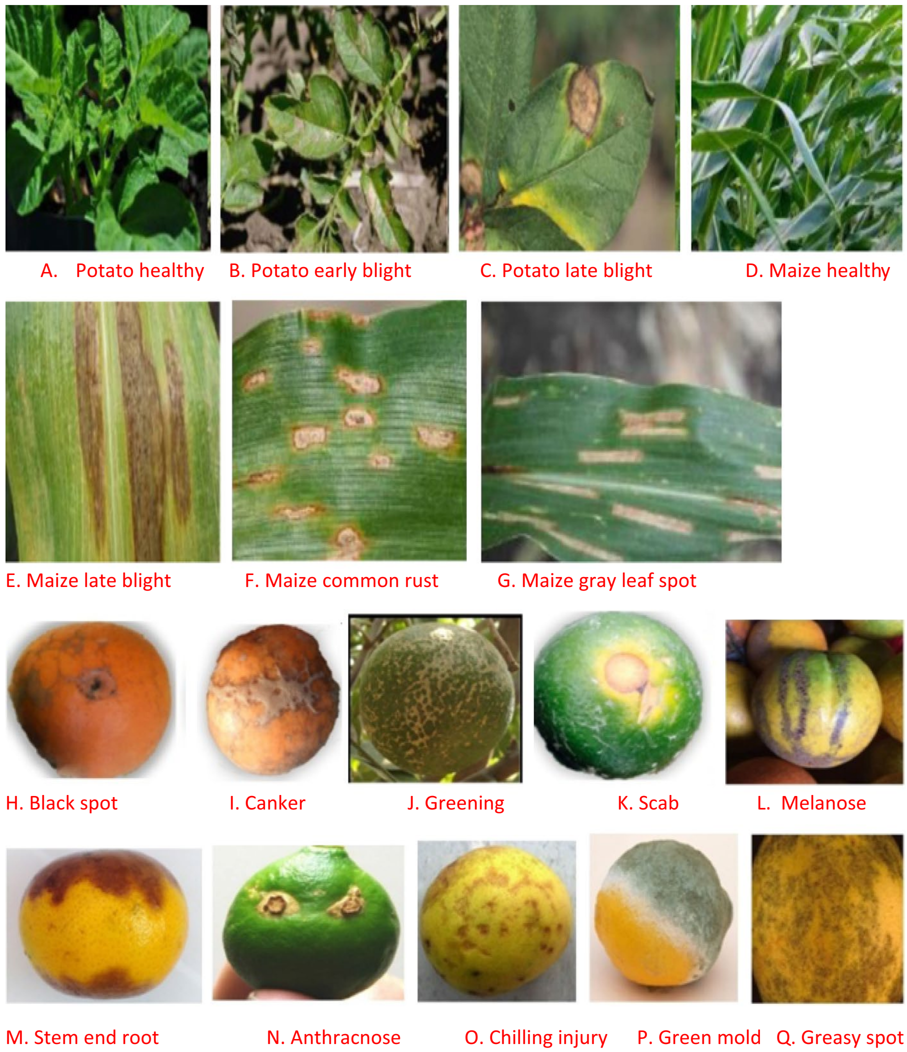

Fig. 3 Different images from other datasets showing healthy and diseased plant leaves [29, 30]

of each feature's conditional probability. This theory works fairly well in many classification problems, even though it usually does not hold in a real-life setting.

B. The KNN Technique It is a nonparametric, supervised ML technique commonly applied to pattern recognition [19, 21]. It is predicated on the nearest neighbor rule, which is applied in ML applications to classify data. This method involves training the test pattern using the classifier, and then classifying the test pattern according to how similar it is to each training pattern. The KNN classifier produces a class membership value that it is a member of. The object is allocated to the most widely used class labels among its k-nearest neighbors based on the plurality vote of its neighbors. It functions similarly to an instance-based learning model, with locally approximated operations and distinct computations throughout the classification process.

C. The DT Technique In supervised learning, it is a supervised classification and regression algorithm that creates classifiers by splitting the data into multiple smaller groups (tree structure) according to which division creates the greater disproportion

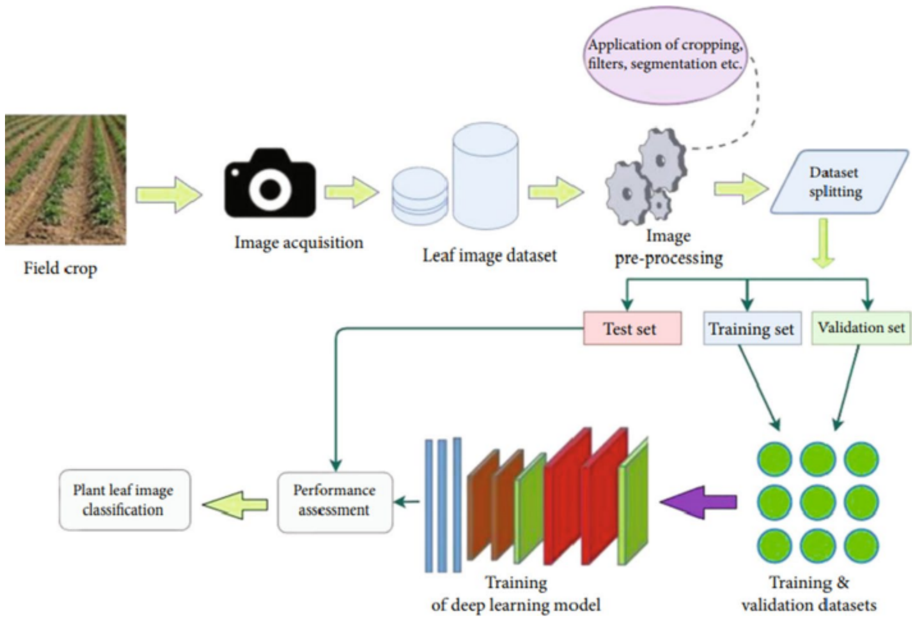

Fig. 4 Computer vision-based techniques for plant disease detection and classification[21]

[19, 21]. One of the often utilized attribute selection metrics that are frequently employed as disparity measurements is the Gini index, also known as entropy. One benefit of this method is that it may make it simple for humans to interpret the results. If the tree could have trained without being limited by its depth, a DT may generate very little training error. Several DT variations, including ID3, C4.5, and CART, are widely employed in various data mining and ML applications.

D. The SVM Technique The separating hyperplane defines this supervised ML classifier. In high-dimensional space, this technique determines the ideal hyperplane that maximizes the margin between the data points of the two classes [19, 21, 29]. The kernel tricks that are helpful for nonlinear classification are an attribute of SVM. Obtaining more distinct features in the high-dimensional feature space is highly anticipated. Several general functions, including the linear, polynomial, and radial basis functions, can be used to transform the features to finish it. The feature space's dimensions could grow significantly as a result of feature transformation. As such, it lengthens the classification process's training period. By calculating the dot products, it might change the features into higher proportions without changing the feature set.

E. The RF Technique It is a collection of learning techniques for randomized DT classifiers [19, 21]. During training, it is run by building several DTs. Based on each classification tree's vote, the class labels of the testing dataset are calculated. The class labels with the highest votes by the classification trees determine the classifier's final result. This approach attempts to produce an uncorrelated forest of trees that will predict performance more accurately than that of the individual tree by using bagging and randomness of features during the building of each tree.

Deep learning (DL) techniques or algorithms

A. The CNN Technique Deep feed-forward neural networks are used by the CNN to analyze multidimensional data. The CNN learns channels that are activated after it classifies a particular highlight at some spatial positioning information [19, 21, 24, 29]. The number of epochs utilized in the implementation of various convolution filters with dimensions of 2×2 and 3×3 determines their accuracy. This is contingent upon the filter's dimensions. Several pre-trained architectures, including VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet, and DenseNet121, are available for use with the CNN approach.

B. The ANN Technique A neural network is a model that mimics the information processing capabilities of a biological system, such as the brain [19, 21, 29]. Coefficients link artificial neurons, also known as processing elements (PEs), to create a network structure. Experience leads to the discovery of data patterns and linkages rather than their programming. Because ANNs can comprehend complex data, they can be utilized to extract patterns from it.

Related works

In this study, the author has analyzed the literature on various plant leaf disease detections and classifications, as well as the models/techniques that have been used.

According to [1], DL-based solutions for real-time insect detection and identification in the soybean crop have been proposed. The performances of various transfer learning (TL) models were investigated to determine the feasibility and reliability of the proposed approach for determining the insect's identification and detection accuracy. The proposed approach achieved 98.75%, 97%, and 97% accuracy using YoloV5, InceptionV3, and CNN, respectively. Among these, the YoloV5 algorithm performs quite well in the solution and can run at 53 fps, making it suitable for real-time detection. Furthermore, a dataset of crop insects was collected and labeled by mixing images taken with various devices. The proposed study reduced the workload of the producer, was considerably simpler, and produced better results. The authors of [14] have proposed a system that uses DL approaches to classify and detect plant leaf diseases. They collected the images from the PlantVillage dataset website. They used the CNN to classify plant leaf diseases in the suggested method. There were 15 classes, including 12 classes for diseases of various plants that were found, such as bacteria, fungi, and so on, and three classes for healthy leaves. As a result, they achieved high accuracy in both training and testing, with an accuracy of 98.29% in training and 98.029% in testing for all data sets used.

In the study of [25], an effective method for recognizing and identifying rice plant disease based on the size, shape, and color of lesions in a leaf image has been presented. The suggested model uses Otsu's global threshold technique to perform image binarization to remove image background noise. To detect the three rice diseases, the proposed technique based on a fully connected CNN was trained using 4000 image samples of each diseased leaf and 4000 image samples of healthy rice leaves. The results revealed that the proposed fully connected CNN approach was fast and effective, with an accuracy of 99.7% on the dataset. This accuracy far exceeded that of the existing plant disease detection and classification methods. The authors of [26] have presented a model based on CNN to identify and classify tomato leaf disease using a public dataset and complement it with images taken on the country's farms. To avoid overfitting, generative adversarial networks were used to generate samples that were similar to the training data. The results reveal that the proposed model performed well in the detection and classification of diseases in tomato leaves, with an accuracy greater than 99% in both the training and test datasets.

The authors of [29] have used the dataset "PlantVillage" to depict four bacterial infections, two viral diseases, two mold diseases, and one mite-related ailment. Images of unaffected leaves were also shown for a total of 12 crop species. For the development of prediction models, ML approaches such as SVMs, grey-level co-occurrence matrices (GLCMs), and CNNs were used. AI for classification has evolved alongside the development of the backpropagation of ANNs. Based on the real-time leaf images gathered, a KMC operation was also performed to detect diseases. Finally, the proposed approach achieved an overall accuracy of 99% and 98% for rice trees and apples, respectively, and 96%, 94%, 95%, and 97% for tomato trees. Multi-class classification problems, such as the one in this study, were evaluated using precision, recall, and f-measure metrics for a set containing only one symptom pool for each class. The authors of [39] have proposed the use of an enhanced CNN technique to detect rice disease. DNNs have had a lot of success with image classification tasks. In this study, they have demonstrated how DNNs can be used for plant disease detection in the context of image classification. Finally, this research compares existing techniques in terms of accuracy of 80%, 85%, 90%, and 95% for TL, CNN + TL, ANN, and ECNN + GA techniques, respectively. The work in [40] has addressed numerous ML and DL techniques. SVM, KNN, RF, LR, and CNN were the ML approaches used in the study effort for disease prediction in plants. Then, a comparison of ML and DL approaches was carried out. Among the ML techniques, the RF has the best accuracy of 97.12%; however, when compared to the DL model presented in the study, the CNN technique has the highest accuracy of 98.43%.

The capacity to identify rice leaf disease was limited by the image backgrounds and the conditions under which the images were acquired [41]. DL models for automated identification of rice leaf diseases suffer significantly when evaluated on independent rice leaf disease data. The results of well-known and frequently used TL models for detecting rice leaf disease were examined in this study. There were two methods for accomplishing this: frozen layers and fine-tuning. The DenseNet169 findings produced an excellent testing accuracy of 99.66%, and when the results of the fine-tuned TL models were analyzed, Xception performed well and achieved 99.99% testing accuracy. The authors of [42] have presented Ant Colony Optimisation with Convolution Neural Network (ACO-CNN), a novel DL technique for disease detection and classification. ACO was used to assess the effectiveness of disease diagnostics in plant leaves. The CNN classifier was used to subtract color, texture, and plant leaf arrangement geometries from the given images. Some of the effectiveness metrics used for analysis and providing a proposed method demonstrate that the proposed approach outperforms previous techniques with an accuracy rate. Aoncert measurements were utilized for the execution of these approaches. Finally, the ACO-CNN model outperformed the C-GAN, CNN, and SGD models in terms of accuracy, precision, recall, and f1-score. The accuracy rates of C-GAN, CNN, and SGD were 99.6%, 99.97%, and 85%, respectively. The accuracy rate in the ACO-CNN model was 99.98%; therefore, precision, recall, and F1-score have higher rates in the ACO-CNN technique compared to other models, and the F1-score has the highest rate compared to other models. The authors of [43] have presented a DL model (PPLCNet) that includes dilated convolution, a multi-level attention mechanism, and GAP layers. The model used novel weather data augmentation to expand the sample size to enhance the generalization and robustness of feature extraction. The feature extraction network uses saw-tooth dilated convolution with a configurable expansion rate to extend the perceptual field of the convolutional domain, effectively addressing the problems of insufficient data information extraction. The lightweight CBAM attention mechanism was located in the feature extraction network's middle layer. It was used to improve the model's information representation. By reducing the number and complexity of parameters computed by the network, the GAP layer prevents overfitting of the model. The validation of the retained test dataset reveals that the PPLC-Net model's recognition accuracy and F1-score were 99.702% and 98.442%, respectively, and that the number of parameters and FLOPs were 15.486 M and 5.338G, respectively, which can meet the requirements of accurate and fast recognition. Furthermore, the proposed integrated CAM visualization approach fully validates the efficiency of the proposed model. According to the study [44], an effective CNN model was proposed to categorize tomato leaf diseases and detect the name of the disease affecting tomato leaves. An approach to a 2-dimensional Convolutional Neural Network (2DCNN) model with 2-Max Assembling covers and completely related layers has been proposed. The experimental results show that the model was successful enough to detect the disease with an accuracy of 96% when compared to other classification models such as SVM, VGG16, Inception V3, and Mobile Net CNN model.

To extract different features [45] have used model engineering (ME). To improve feature discrimination and processing speed, several SVM models were used. In the training process, the kernel parameters of the radial basis function (RBF) were computed depending on the selected model. Six leaf image sets encompassing healthy and sick leaves of apple, corn, cotton, grape, pepper, and rice were analyzed using PlantVillage and UCI databases. Accordingly, the categorization procedure yielded almost 90,000 images. The findings of the experimental implementation phase reveal the potential of a powerful model in classification activities, which would be useful for a variety of future leaf disease diagnostic applications in the agricultural business. In terms of stability, the dilated learning model outperforms the typical ResNet-18 design. On the test set, the model had an average accuracy of 98.5% for leaf disease recognition models. In recognizing grape or cotton leaf diseases, a test set accuracy of 97.93% is less than the proposed structure's accuracy of 97.93%. The authors of [46] have presented an image segmentation algorithm for the automatic detection and classification of plant leaf diseases. It also includes an overview of various disease classification techniques that can be used to detect plant leaf disease. The genetic algorithm was used for image segmentation, which was vital for disease detection in plant leaf disease.

The ensemble classifiers (EC) in [47] were developed by using various approaches to preparation, feature extraction, and classification. The performance of these multiple ensemble techniques was then compared to select the best ensemble classifiers. The suggested technique's precision and reliability were tested in both controlled laboratory settings and real-world conditions using two databases, namely PlantVillage and Taiwan tomato leaves. The top EC, which achieved 96% accuracy, was determined by the consideration of shadow, brightness fluctuations, disease similarities, background clutter, multiple leaves, and diverse textures. Here, the proposed ensemble models were presented and linked to several DL techniques. Furthermore, the proposed solution outperformed the most recent state-of-the-art DL technique.

The authors of [48] have proposed a hybrid DL approach for the early detection and classification of tomato plant leaf diseases. A CNN, a convolutional attention module (CBAM), and SVM were combined in the hybrid system. The proposed approach was evaluated using a database of tomato leaf images. The suggested model can initially detect nine distinct tomato diseases; however, it is not limited to this. The obtained findings were highly encouraging, with an accuracy of up to 97.2%, which can be improved by improving learning processes. Here, the proposed approach outperformed better than the state-of-the-art DL approaches.

The proposed system was lightweight and efficient, so the farmer may install it on any smart device with a digital camera and processing capabilities. A farmer can detect any disease immediately with a little training, allowing them to take timely preventive measures.

The authors of [49] have tested and presented their work on a publicly available standard database, the PlantVillage Kaggle dataset. More specifically, they obtained mAP and accuracy values of 98.10% and 99.97%, respectively, as well as a test time of 0.23 s. Both qualitative and quantitative results confirmed that the presented solution was robust for plant leaf disease detection and could replace manual systems. Moreover, the suggested method showed a low-cost solution to tomato leaf disease classification that was robust to several image transformations, such as variations in the size, color, and orientation of the diseased portion of the leaf. Furthermore, the framework can locate the affected plant leaves when there are variations in blurring, noise, chrominance, and brightness. The authors have confirmed that, based on the reported data, their technique was robust to several tomato leaf disease classifications under varying image-capturing conditions. The proposed work in [50] has employed an aggregated loss function by combining triplet and cross-entropy loss with MobileNetV2 as a basis model for the effective classification of plant disease using small samples. For the evaluation of the proposed study, two publicly available datasets (PlantVillage with 54,303 leaf samples and Plantdoc with 2598 leaf samples) were used. To partition the dataset into the source and target domains, different domain splits were examined, and a large quantity of testing was conducted on the target dataset using various sample sizes.

For the analysis of the PlantVillage dataset, four domain splits were considered, and it was found that using the proposed aggregated loss and the lightweight transfer learning (TL) model for the target domain data (K-ways, N-shot), an average improvement in accuracy was 1.49% for split-1, 16.25% for split-2, 2.9% for split-3, and 2.1% for split-4 when compared to previous work. For the plantdoc dataset, two domain splits were evaluated, yielding an accuracy of around 81% with 30 samples and more than 40% with only one sample. Using several evaluation measures such as loss functions, execution time, model size, and model parameters, the suggested work was compared to other state-of-the-art research works.

According to [51], a DL approach for early ginger disease detection from the leaf was proposed through different phases. After collecting 7014 ginger images with the help of domain experts from different farms, a DL approach has been implemented. The acquired data was subjected to various image preprocessing to design and develop a DL model capable of detecting and classifying various scenarios. The experimental results showed that the proposed approach was useful for detecting ginger diseases, especially bacterial wilt. With a test accuracy of 95.2%, the proposed model can correctly detect the given image. The results showed that the DL approach provides a fast, affordable, and easily deployable strategy for ginger disease detection, making the model a useful early disease detection tool. This analysis was also extended to develop a mobile app to assist a large number of ginger farmers in developing countries.

The work in [52] has examined an alternative approach for developing a disease detection model supported by leaf classification using deep convolutional networks (DCN). Growth in computer vision presents an opportunity to broaden and boost precision crop protection practice, as well as expand the market for computer vision applications in precision agriculture, a unique form of training, and thus the technique used allows for quick and direct implementation of the system in practice. The database used in this research work contains 77,000 images of healthy and diseased plant leaves. They were able to train a CNN model for classifying plant diseases, determining whether they were present or not, and then another model was trained with YOLOv7 to detect the disease, with the trained classification model achieving an accuracy of 99.5% and the detection model achieving mAP, precision, and recall of 65%, 59%, and 65%, respectively.

The authors of [53] have presented a DL-based CNN solution for automatically classifying and distinguishing cotton leaf diseases. There has been a lot of study done on leaf diseases that were common in many crops, but this work offered an effective and reliable method for identifying cotton leaf disease. The proposed method successfully classified and detected three significant cotton leaf diseases, which were difficult to control if not detected early. The proposed model for the identification and classification of cotton leaf diseases has used CNN, with training and testing accuracy of 100% and 90%, respectively.

The research works of [54] have shown the detection of various diseases using hybrid image processing and decision tree (DT) techniques. The images were from Jimma and Zegie in Southern Ethiopia. Backpropagation artificial neural network (BPNN) and DT approaches were used. A total of 9100 images were collected. 70% of them are used for training, while the remaining 30% are used for testing. When a decision tree and a BPNN with a tanh activation function were coupled the overall accuracy was 94.5%.

The authors used three different types of data sets [55] by including original images of RGB, blending images, and a mixture of RGB images and blending images. The classification results produced by a mixture of RGB images and blending images outperformed others, with a Genuine Acceptance Rate (GAR) of 96.7%, followed by a percentage of False Acceptance Rate (FAR) values of 3.3% and False Rejection Rate (FRR) values of 3.3%.

The authors of [56] have proposed a technique in the literature that reports that have good detection accuracy but have a low reliability. This work has presented a DL-based method for detecting tomato disease using image segmentation. The authors create leaf masks with the VIA tool. The proposed method segments images using a customized U-Net model and then it classifies the segmented images into ten categories using a convolutional network. The accuracy of 98.12% proved that it was a promising technique for automated tomato disease detection, which can help to improve tomato production and reduce crop loss.

According to [57] an autonomous method for detecting and classifying coffee plant disease becomes very crucial for better productivity. Here, the DL model was trained using 1120 images from the Wolaita Sodo agricultural research center, and an augmentation method was used to deal with data over-fitting. A total of 3360 images were used. They have compared training from scratch and TL strategies to get the best results during the classification of such diseases. As a result, training from scratch achieves an accuracy rate of 98.5%, whereas transfer-based learning achieved rates of 97.01% and 99.89% when using Mobilnet and Resnet50, respectively. The pre-trained Resnet50 model outperformed other approaches for the classification of images.

The authors of [58] have proposed a method for detecting tomato plant disease using a DL-based system and image data from plant leaves. In this research, they have used the InceptionNet model and a DL architecture based on a recently developed CNN that was trained over 18,161 segmented and non-segmented tomato leaf images using a supervised learning approach to detect and recognize various tomato diseases. In this work, two state-of-the-art semantic segmentation models, U-Net and Modified U-Net, were used to detect and segment disease-affected regions. By 98.66%, 98.5% IoU score, and 98.73% on the dice, the Modified U-net segmentation model exceeds the standard U-net segmentation model. Here, the InceptionNet1 achieved 99.95% accuracy for binary classification problems and 99.12% accuracy for classifying images with six segments; the InceptionNet technique outperformed the Modified U-Net model in terms of accuracy. The experimental findings of their proposed method for classifying plant diseases showed that it outperformed existing methods in the literature.

The authors of [59] have proposed a pipeline for autonomous identification of tomato leaf diseases using three compact CNNs. The authors have used TL to extract deep features from the CNNs' final fully connected layer for more condensed and high-level representation. Next, it merges elements from the three CNNs to take advantage of each CNN structure. Following that, a hybrid feature selection approach was used to select and build a comprehensive feature set of lower dimensions. The tomato leaf disease identification approach has been utilized for six classifiers. The results showed that the KNN and SVM techniques achieved the highest accuracy of 99.92% and 99.90% using only 22 and 24 features, respectively. The proposed pipeline's experimental findings were also compared with existing research studies for tomato leaf disease classification, confirming its competitive potential.

The authors of [60] have combined features taken from input images using two recent pre-trained CNN models, ResNet50 and MobileNet, using a deep feature concatenation (DFC) technique. As a result, they have proposed MobiResNet: a neural network that was a concatenation of the ResNet50 and MobileNet models for overall prediction capability improvement. 5400 olive leaf images were taken from an olive grove using a remote-controlled agricultural unmanned aerial vehicle (UAV) equipped with a camera to create the dataset used in the study. The overall performance of the MobiResNet model was 97.08%, demonstrating its superiority over ResNet50 and MobileNet, which attained classification accuracies of 94.86% and 95.63%, respectively.

The PlantDet, a robust new deep ensemble model built on InceptionResNetV2, EfficientNetV2L, and Xception, has been proposed in [61]. The PlantDet not only solves under-fitting problems, but it also nourishes performances for a scarce dataset with a sparse number of different background image datasets. PlantDet integrates efficient data augmentation, pre-processing, a Global Average Pooling layer, a Dropout mechanism, L2 regularizes, a PRelu activation function, Batch Normalization layers, and more Dense layers, which make the model more robust in comparison to all existing models and assist in dealing with under-fitting and overfitting problems while maintaining high performance.

PlantDet outperformed the previous best model for the rice leaf dataset, with 98.53% accuracy, 98.50% precision, 98.35% recall, 98.42% F1-score, and 99.71% specificity. PlantDet also outperformed all available base models, including several robust ensemble models, on the Betel leaf dataset. Finally, Grad-CAM and Score-CAM were accomplished using the Xception approach to explain model performances, specifically how DL models function for this complicated dataset. In terms of localizing the predicted area, Score-CAM somewhat exceeded Grad-CAM++.

The authors of [62] have introduced a strong plant disease classification system using a Custom CenterNet framework with DenseNet-77 as a base network. The presented method consists of three steps. Annotations were developed in the initial phase to determine the region of interest. Second, an enhanced CenterNet was presented, with DenseNet-77 recommended for deep key point extraction. Finally, several plant diseases were detected and classified using the one-stage detector CenterNet. They used the PlantVillage Kaggle database to do the performance analysis, which was the standard dataset for plant disease and challenges in terms of intensity variations, color changes, and differences in the shapes and sizes of leaves. Both qualitative and quantitative analyses confirmed that the presented method was more proficient and trustworthy than other latest approaches in identifying and classifying plant diseases.

The goal of [63] was to assist farmers in correctly identifying early-stage diseases and informing them about these diseases. To properly describe and categorize tomato diseases, CNN was used. The entire experiment was carried out using Google Colab and a dataset including 3000 images of tomato leaves affected by nine different diseases as well as a healthy leaf. Firstly, the input images were first pre-processed, and the targeted area of images was split from the original images. Secondly, the images were further processed with different CNN model hyper-parameters. Finally, CNN extracts other features from images like as colors, texture, and edges, among others. The results showed that the proposed model predictions were 98.49% accurate.

The authors of [64] have proposed a tomato leaf disease classification method using TL and feature concatenation. The authors extract features from MobileNetV2 and NASNetMobile using pre-trained kernels (weights), then concatenate and reduce the dimensionality of these features using kernel principal component analysis. They then feed these features into a conventional learning algorithm. The experimental results confirmed the efficiency of concatenated features in improving classifier performance. The authors have tested the three most common traditional ML classifiers, RF, SVM, and multinomial LR, and found that multinomial LR performed the best, with an average accuracy of 97%.

The authors of [65] have proposed a novel method for improving broadleaf plant categorization by combining filtered features collected by Local Binary Pattern operators and features retrieved by plant leaf contour masks. Noise in plant images was filtered using morphological operators of opening and closing. A testbed system was used to collect images at four stages of growth. Local binary pattern features based on masks were combined with filtered features and with a coefficient of k. SVM with radial basis function kernel was used to classify crops and weeds. By investigating optimal parameters, this method achieved a classification accuracy of 98.63% with 4 classes in the "bccr-segset" dataset published online, compared to a previously reported method's accuracy of 91.85%.

Directional Local Quinary Patterns (DLQP) as a feature descriptor for plant leaf disease detection and SVM as a classifier were investigated in [66]. The DLQP as a feature descriptor was being used for the first time in horticulture for disease detection. DLQP gives directional edge information by calculating the grey-level difference between the reference pixel and its neighboring pixel value by involving computation of their grey-level difference based on quinary value (− 2, − 1, 0, 1, 2) in the 0o, 45o, 90o, and 135o directions of a specified window of a plant leaf images. They have used a research-oriented PlantVillage dataset of tomato plant (3900 leaf images) with 6 diseased classes, potato plant (1,526 leaf images), and apple plant (2600 leaf images) with 3 diseased classes to examine the robustness of DLQP as a texture descriptor. Accuracy rates of 95.6%, 96.2%, and 97.8% were obtained for the aforementioned crops, which were higher when compared to classification on the same dataset using other standard feature descriptors such as Local Binary Pattern (LBP) and Local Ternary Patterns (LTP). Furthermore, the proposed method's effectiveness was demonstrated by comparing it to existing algorithms for plant disease phenotyping.

The authors of [67] have developed an algorithm for detecting and preventing disease spreading to the entire crop, which results in excellent quality crop production. The database of various leaf images was created and processed using KMC image segmentation, and textural analysis of leaf images was performed using GLCM. After ranking their attributes using an information gain algorithm, the SVM classifier was used to classify the feature-extracted images. A graphical user interface (GUI) has been developed to portray the various stages of the image processing algorithm and to detect the two leaf diseases.

The authors of [68] have proposed a DL-based technique for detecting tomato disease that uses the Conditional Generative Adversarial Network (C-GAN) to generate synthetic images of tomato plant leaves. Following that, a DenseNet121 model was trained on synthetic and real images using TL to classify tomato leaf images into ten disease categories. The proposed model has been thoroughly trained and tested using the publicly available PlantVillage dataset. For tomato leaf image categorization into 5 classes, 7 classes, and 10 classes, the suggested method achieved an accuracy of 99.51%, 98.65%, and 97.11%, respectively. Accordingly, the proposed methodology outperformed the existing methodologies.

The authors of [69] have focused on supervised machine learning approaches such as NB, DT, KNN, SVM, and RF for maize plant disease detection using plant images. The aforementioned classification techniques were analyzed and compared to determine the suitable model with the highest accuracy for plant disease prediction. When compared to the other classification techniques, the RF algorithm has the highest accuracy of 79.23%.

The authors of [70] have proposed a new method of assembling TL models to detect rice plants and categorize diseases using images. This model detects the three most frequent rice crop diseases: brown spot, leaf smut, and bacterial leaf blight. The TL, in general, uses pre-trained models and provides higher accuracy for image datasets. Additionally, assembling machine learning algorithms (combining two or more ML algorithms) aids in reducing generalization errors and making the model more robust. EL was becoming more popular since it minimizes generalization errors while also making the model more robust. With an accuracy of 96.42%, they proposed a novel model that ensembles three TL models: InceptionV3, MobileNetV2, and DenseNet121.

A newly conducted research paper microscope called Foldscope was used [71] to identify early blight disease in tomato leaves. To assess the severity of early blight disease in tomato leaves, the study used a deep residual network 101 (ResNet101) of CNN. The model's dataset was trained using an open database, namely the PlantVillage dataset for mild, moderate, and severely infected tomato leaves, as well as healthy tomato leaves. The ResNet101 architecture's performance was compared to that of other pre-trained CNN architectures, including Visual Geometry Group 16 (VGG16), VGG19, GoogleLeNet, AlexNet, and ResNet50. The deep ResNet101 architecture achieved the highest accuracy of 94.6% among these networks.

The authors of [72] have proposed a lightweight TL-based technique for detecting disease in tomato leaves. It uses an efficient pre-processing method to improve classification by enhancing the leaf images with illumination correction. For effective prediction, the system extracts features using a hybrid model composed of a pre-trained MobileNetV2 architecture and a classifier network. To avoid data leaks and handle the class imbalance issue, traditional augmentation procedures were substituted by runtime augmentation. They trained and tested on the PlantVillage dataset. Finally, the proposed architecture attained a 99.30% accuracy.

The authors of [73] have developed methods for detecting and classifying plant disease using diseased plant leaves. In this study, they used four different DL models (InceptionV3, InceptionResnetV2, MobileNetV2, and EfficientNetB0) to classify plant diseases using images of healthy and diseased plant leaves. They used the standard PlantVillage dataset with 53,407 images recorded under laboratory conditions to train and test the classifier. They used accessible datasets to train models that included 14 different plant species, 38 different categorical disease groups, and healthy plant leaves. Using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, the implemented models achieved disease classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56%, respectively, which was higher than that of traditional handcrafted-feature based techniques. Finally, EfficientNetB0 achieved the maximum successful classification accuracy of 99.56%, with significantly less training time than the InceptionV3, InceptionResNetV2, and MobileNetV2 designs.

A DCNN technique was developed by [74] to integrate an attention mechanism that can better adapt to the diagnosis of a range of tomato leaf diseases. The network structure that was implemented primarily consists of residual blocks and attention extraction modules. The model can extract complex aspects of numerous diseases with high accuracy. The dataset was derived from the most widely used publicly available PlantVillage dataset. It was also found that, when compared to another model, the SE-ResNet50 was better suited for the identification of tomato leaf diseases. On the tomato leaf diseases dataset, the suggested model achieved an average identification accuracy of 96.81%, according to the experiment findings.

The authors of [75] have focused on identifying tomato plant leaf disease using image processing techniques based on image segmentation, clustering, and open-source algorithms. Using the image classifier technique that has been implemented, the comparison image was classed as a disease-affected or normal leaf. Other algorithms that can be used include ANN, FL, and hybrid algorithms. All of this contributes to a reliable, safe, and accurate leaf disease system with a focus on tomato plants' leaves. The method was evaluated using OpenCV, one of the most used libraries for computer vision applications. Finally, when compared to other neural networks, they attained an accuracy of 98% using the proposed technique.

The authors of [76] have used a DNN for real-time tomato plant leaf disease image classification. They were used to develop a framework that uses a series of frameworks to classify the leaf disease, including image acquisition, feature extraction, and the tomato plant. The MatLab platforms were used to analyze the DNN classification performance on tomato leaves, which consists of 1,500 images of healthy and diseased leaves, respectively. The tomato leaf images were well-ranked using the DNN DL technique. The DNN results were 86.18% more accurate than existing models.

The authors of [77] have developed a DL technique for classifying tomato plant disease by combining CNN pre-trained models and fine-tuning them. The purpose of this work was to use multiple performance indicators to compare the performance of AlexNet, GoogleNet, Inception V3, ResNet 18, and ResNet 50. When these models were compared, the advantages were that CNNs do not require any tiresome pre-processing and have a faster convergence rate and lucrative training results. The model used in this study was capable of classifying nine diseases in tomato leaves from the healthy class, whereas the GoogleNet model with 22 layers can achieve 99.72% tomato disease classification using the TL training method. When compared to the other architectures, Inception V3 had the lowest performance.

The authors of [78] have proposed an advanced classification model to detect and classify tomato leaf disease. Before classification with KNN, a training dataset of 450 images was used, and image features were retrieved using different models. The AlexNet model had a classification accuracy of 76.1%, which was the highest when compared to other models. In general, CNNs, such as AlexNet for feature extraction and KNN for classification, were used. Using three pre-trained CNN models, the authors of [40] used TL and feature extraction techniques to estimate the disease severity of tomato late blight disease.

The authors of [79] have developed a computer vision way to identify the condition by recording leaf images and recognizing the disease's probability. A DL technique was used in this study to develop a robust judgment that spans a wide range of leaf appearances. The MobileNet V2, a small DL architecture, has been fine-tuned to detect three types of tomato disease. When MobileNet V2 was trained using Adagrad with a batch size of 16, it achieved the best classification performance. The system was put through its paces on 4,671 images from the PlantVillage dataset. The findings suggested that MobileNet V2 can detect the disease with greater than 90% accuracy.

The authors of [80] have described how to develop a hybrid of SVM and LR methods to predict powdery mildew disease in tomato plants. The SVM was used here to minimize noise in the data before it was supplied to the LR classifier. The adaptive sampling-based noise reduction (ANR) method was used to reduce noise using an SVM classifier. In this study, a real-world tomato Powdery Mildew Disease (TPMD) dataset was used to create a prediction model using the proposed strategy. Individual SVM and LR algorithms were also employed to create the prediction models. According to the results, the suggested classifier outperformed SVM by 3.06% and LR by 5.35%, with an accuracy of 92.37%.

The authors of [81] have described a novel plant leaf disease identification model based on a DCNN. The DCNN model was trained in this study using an available dataset containing 39 different classes of plant leaves and background images. They also employed six data augmentation techniques: image flipping, gamma correction, noise injection, principal component analysis (PCA), color augmentation, rotation, and scaling. Different training epochs, batch sizes, and dropouts were used to train the proposed model. They also compared them to common TL algorithms; the new model outperformed the others when using validation data. The proposed model had a classification accuracy of 96.46%.

The authors of [82] have proposed a technique that outperformed the existing ML approaches in terms of accuracy. They have presented a computer vision framework for identifying and classifying plant diseases. The proposed technique extracts local tri-directional patterns (LTriDP) from images of plant leaves of various types. The classification was done using multiclass SVM, and the studies were done on a tomato leaf dataset with five different classes. Finally, experimental findings demonstrate that the proposed framework outperforms competing approaches based on regularly used feature descriptors, achieving an overall accuracy of 94%.

The authors of [83] have proposed a DCNN model based on TL to identify tomato leaf disease. In this case, the model detects disease by using real-time and stored tomato plant images. In addition, the suggested model's performance was evaluated using adaptive moment estimation (Adam), stochastic gradient descent (SGD), and RMSprop optimizers. The experimental results showed that the suggested model, which used the TL approach, was effective in the automated categorization of tomato leaf disease. The suggested model for the Adam optimizer, which uses a TL strategy, yields a 99.55% accuracy, which is 0.54% higher than RMSprop and 17.78% higher than SGD optimizers.

The authors of [84] have developed a DL-based technique to detect the disease. A CNN-based technique was used here for disease detection and classification. There were three convolution layers, three max-pooling layers, and two fully linked layers in this model. The experimental findings showed that the proposed model outperformed the pre-trained models VGG16, InceptionV3, and MobileNet. The classification accuracy varies from 76 to 100% depending on the class, and the suggested model's average accuracy is 91.2% for the 9 diseases and 1 healthy class.

The authors of [85] have proposed many ML methods and CNN models for the identification of tomato crop disease. A simpler CNN model with eight hidden layers was proposed. They used the publicly available PlantVillage dataset, and the proposed lightweight model outperforms established ML approaches. While KNN provides the best accuracy of 94.9% in a traditional ML technique, VGG16 in pre-trained models achieves the best accuracy of 93.5%. Finally, the proposed model outperformed PlantVillage on other datasets, with an accuracy of 98.7%.

The authors of [86] have provided an overview of various techniques for detecting and classifying plant leaf disease. The study found that image processing approaches can give an effective and accurate method of classifying plant leaf disease. The authors of [87] have used GLCM, KMC, and SVM algorithms to classify diseases on images of citrus leaves. Using their proposed strategy, the researchers achieved a classification accuracy of 90%.

The authors of [88] have developed a method for detecting disease using image processing techniques in wheat fields. This study has made a significant contribution to the automation of agricultural methods and processes. The authors of [89] have developed a computer-aided image-processing approach for detecting plant leaf diseases. To classify cucumber leaf diseases, the authors have used KMC and SVM classifiers. The researchers in [90] carried out a study of five different modern DL models. With an accuracy of 86.799%, ResNet101V2 produced the best result. The authors of [91] have proposed a model for identifying paddy leaf diseases. The authors achieved 97.5% recognition accuracy by combining the SVM classifier and DCNN algorithms.

The authors of [92] have proposed a model to detect groundnut leaf disease using the KNN algorithm. According to the researcher's perspective, plant diseases can be caused by fungi, bacteria, viruses, and other organisms. Plant diseases can be identified using image processing approaches based on images of affected leaves [93]. The authors achieved an accuracy of 88.89% using SVM and KMC. Agricultural plant diseases that impact farmlands cause a decrease in agricultural crop results volume. Early disease detection controls the disease and prevents it from spreading throughout the farm [94]. A computerized approach for classifying soybean plants was used to develop a decision support system that provides users with advice. The categorization accuracy of the authors was 93.79%.

To identify plant diseases, a new architecture called plant disease detection neural network (PDDNN) was a successful detection system for plant diseases using a CNN model [95].

Farmers cannot effectively identify plant disease with their naked eyes, and if the disease is not uncovered promptly, it may harm the entire farmland or even a neighboring farm. Accordingly, modern computer technology is required for efficient and early plant leaf disease detection. The architectures of CNN were used to achieve an overall classification accuracy of 86.00% for AlexNet and GoogleNet techniques. Every country's economic fortune is determined by the quality and quantity of its crop production. By classifying the disease at an early stage, production can be considerably increased. According to [96], the technology ensures that the naked eye wastes time and resources. The technology ensures success by allowing for faster and more accurate identification of plant leaf disease. Cotton leaf disease was detected using a DCNN. The authors implemented their approach and confusion matrix in MATLAB to classify disease types. Their results showed an average accuracy of 96%.

The authors of [97] have proposed using image processing and artificial neural approaches to identify disease in brinjal leaf plants. For segmentation, they used the KMC algorithm, and for classification, they used the ANN.

The authors of [98] have done a study that used DL to detect tomato leaf diseases. To detect tomato plant disease, they used an algorithm that ran in real-time. The authors of [99] have used CNN to investigate tomato leaf disease. The authors attained a 97% classification accuracy.

Monitoring large farms with automated approaches can be useful to farmers because it reduces the tedious work of close observation by experts. In classifying plant leaf disease, automatic systems used image segmentation algorithms [100]. They have used MATLAB for experimentation purposes.

The authors of [101] have proposed a new image identification system based on several linear regressions and an enhanced histogram segmentation algorithm. Their method worked well since the appropriate threshold could be determined automatically. It was important to use digital image processing for vision-based automated prediction of crop plant diseases [102]. The KMC algorithm was used for color segmentation, and the GLCM technique was used for classification. Here, good results and promising performances were achieved. The authors proposed that their technique reduces detection time and labor costs. Using computerized imaging technologies, early detection and identification of plant leaf disease can aid in enhancing agricultural production [103]. The authors examined various ways of detecting leaf plant diseases used by previous researches. Their research provides a critical analysis of various image classification algorithms. To identify crop plant diseases, many disease recognition approaches have been used. Different strategies have been used to increase disease classification recognition rates [104]. When it comes to accurately identifying plant diseases, farmers have limited knowledge. According to recent studies, computerized image classification systems based on CNN structure can aid in addressing the issue of erroneous identifications.

According to [105] datasets for rice plant disease are not easily available. The authors developed their small dataset and achieved a 92.46% accuracy. The authors in [106] have written research that highlights the importance of using image processing techniques to detect plant diseases using images of infected leaves. The researchers developed a software system solution for automatically detecting and classifying images. They have discussed the steps involved in the classifying process, from loading the images to identifying the disease.

Farmers lack a full understanding of leaf plant diseases and must be guided on how to apply computerized image processing methods [107]. The researchers proposed a solution that works with Android applications. The model provides an efficient method for detecting and classifying plant diseases. The CNN was used by the proposed system to classify plant leaf diseases. Accordingly, DL-based disease identification in plants and pests poses a variety of issues in the future. However, feasible answers and general suggestions can be obtained through the practical implementation of different plant leaf disease detection technologies. Adopting technology is required to address the challenges of recognizing and analyzing plant diseases [108]. The authors proposed a system for processing and classifying potato leaf disease images that used various Classifier algorithms to achieve 97.00% classification accuracy.

The authors of [109] have developed a methodology for developing a CNN-based strategy for detecting and identifying plant leaf disease. The CNN and DNN can be used to swiftly and effectively identify crop diseases and their symptoms. The authors of [110] have designed a system that classified guava leaf diseases using a DCNN technique. Their solution achieved 98.74% accuracy by using the AlexNet strategy based on the DCNN model. The authors of [111] have used Inception v3 to develop such an identification model. Three classification metrics were used to evaluate the proposed model. The authors reviewed the identification of plant diseases. They also established that the CNN technique had a higher capacity to produce accurate results.

According to [112],14 plant types and 26 diseases were used to develop a CNN approach for detecting plant diseases. Using AlexNet and GoogleNet, the model obtained a testing accuracy of 99.35%. The authors of [113] have used ANN to develop a model with an 80% classification accuracy on cotton leaf. ANN has been used to classify plant leaf diseases by different researchers. The authors of [114] have carried out a study that used ANN on 169 images. Their approach had a 92% accuracy rate.

Another comparative study was carried out by [115]. Here, various neural networks that have previously been used by various researchers have been investigated and reviewed. The authors established that the most widely used neural networks were ANN and CNN. DL algorithms were accurate in classifying plant diseases. The authors of [116] used CNN to identify diseases in various crop plants with a 98% accuracy. The authors of [117] have used MATLAB to perform research on the automatic classification of plant leaf diseases. The authors experimented on beans and tea leaves, achieving accuracy rates of 98.2% and 98.4%, respectively.

The authors of [118] have conducted a review on the identification of plant leaf diseases using digital image processing approaches. The efficiency of various image processing algorithms has been highlighted. According to the author's point of view, most researchers prefer neural networks to other methods. The authors of [119] have studied groundnut leaf disease using the backpropagation approach to classify four types of diseases. Their work was 97% accurate. The authors of [120] have conducted an extensive review of recent work on plant leaf disease classification using digital image processing technologies. The authors demonstrate that DL methods outperformed conventional approaches when large amounts of data are available.

When it comes to plant leaf disease, neural network classifiers produce greater output and efficiency [121]. The authors have used multi-layer perceptron (MLP) and Radial Basis Function (RBF) to study the wall of Phyllanthus Elegans. Their approaches provided 90.15% and 98.85% accuracy, respectively. The authors of [122] have experimented with four different diseases using cotton and soybean leaves: angular leaf spot, bacterial pustule, bacterial gummosis, and bacterial blight. They were achieved 83%, 80%, 80%, and 70%, respectively. A study on plant leaf disease recognition using CNN and a Bayesian algorithm was performed by [123]. The authors achieved an overall accuracy of 98.9% by using over 20,000 images of potato, tomato, and pepper bells.

The authors of [124] have investigated four grape plant diseases: leaf blight, black rot, stable, and black measles. The authors achieved a total accuracy of 98.7% by combining hybrid CNN with feature reduction. Automatic identification of plant leaf disease using plant leaves was critical in farming. The authors [125] attained a 96% overall accuracy. Using pattern recognition, researchers in [126] reached an accuracy of 90% in the classification of apple leaf disease.

The authors of [127] have proposed an automated strategy for identifying paddy leaf diseases using ML and evolutionary techniques. The model can be used on the Android platform to quickly identify diseases.

According to [128] a customized CNN-based maize plant disease identification model was presented, along with various preprocessing techniques, including contrast-limiting adaptive histogram equalization (CLAHE) on each RGB (Red, Green, and Blue) channel, log transformation, and RGB to HSV (Hue, Saturation, and Variance) image conversion. These trained models were compared to CNN and SVM models that were trained without any preprocessing procedures. The experiments were carried out using the PlantVillage maize crop dataset to determine the effectiveness of the proposed effort. The proposed work had a maximum accuracy of 99.76%. The authors of [129] have achieved an overall accuracy of 98.39% when using GA to classify and analyze unhealthy grape plant leaves. A survey was conducted in [130] to examine several image classification methods that can be used to identify diseases of plant leaves. The authors of [131] have researched different DL approaches used in the classification of plant leaf diseases. The authors used the Weka tool to present a thorough examination of numerous techniques.

The authors of [132] have used the NB classification method to develop a model that can identify diseased sections of plant leaves with an overall accuracy of 97%. The authors of [133] have used the NB algorithm to classify plant leaves. The authors fed the shape and texture of the leaves into the classifier. The CNN model outperformed other classifiers such as KNN, RF, SVM, and DT [134]. The authors achieved 99.58% and 97.66% accuracy in identifying paddy and potato leaf diseases, respectively. Using CNN, the authors of [135] have developed a system that provides a report on detecting banana leaf disease. The authors of [136] have proposed three CNN models to identify guava leaf disease. Here, the third model produced an overall accuracy of 95.61%.

The authors of [137] have developed an ML-based technique for detecting and identifying potato leaf disease. The model's overall accuracy was 95.99%. According to [138], a model for classifying bean leaf diseases was developed. The authors achieved 97% training accuracy and 92% testing accuracy. The authors of [139] have proposed a system for detecting maize leaf disease using improved DCNN. Using DCNN, the authors of [140] developed a method for detecting and classifying purple blotch disease in onions. The accuracy of the model was 85.47%. Several DL models for detecting and identifying plant leaf diseases have been developed. DL algorithms that offer more accuracy make this subject of research interesting [20]. ML and DL technologies have been used in agriculture to increase the product while addressing difficulties [141]. To classify plant leaf diseases, the authors of [142] have presented an attention-based depth-wise neural network with Bayesian optimization (ADSNN-BO). An accuracy of 94.65% was obtained. Using the RF technique, researchers have proposed a model that can detect and classify maize disease. An automatic method for the classification of plant diseases based on the RF algorithm was developed by [143]. The proposed model had a 95% accuracy rate. The authors of [144] developed a hybrid learning model for plant leaf classification. To identify plant leaf diseases, the model used KMC and CNN methods. The model outperformed SVM and CNN with an accuracy of 92.6%.

The authors of [145] have used image SVM to identify sugarcane leaf disease and achieved a classification accuracy of 95%. The authors of [97] have used ANN and KNN approaches to develop a model to identify and classify cassava leaf disease. The model in [146] achieved a classification accuracy of more than 90%.

In the work of [147] the DL and ML techniques were proposed and used to solve binary and multiclass subcategories of plant diseases on four different datasets. The proposed approach produces improved results, with 99.4% accuracy and 99.9% sensitivity for binary classes, and 99.2% accuracy for multiclass. In terms of f-measure, recall, MCC (Matthews correlation coefficient), specificity, and sensitivity, the proposed framework outperformed previous approaches such as LibSVM, SMO (sequential minimal optimization), and DL with activation functions softmax and soft sign.

The authors of [148] have focused on the issue and present a DL-based technique for disease detection and classification in maize crops. Furthermore, the developed technique returns segmented images of affected leaves, allowing them to follow the disease spots on each leaf. A dataset of three maize crop diseases blight, sugarcane mosaic virus, and leaf spot was collected from the University Research Farm Koont, PMAS-AAUR, during different growth stages and under different weather conditions. The data was used to train different models for prediction, such as YOLOv3-tiny, YOLOv4, YOLOv5s, YOLOv7s, and YOLOv8n, with stated prediction accuracy of 69.40%, 97.50%, 88.23%, 93.30%, and 99.04%. The results showed that the YOLOv8n model outperformed the other models in terms of prediction accuracy. With a higher confidence score, this model produced good results in properly localizing the afflicted portion of the leaf. Furthermore, the high-accuracy models have been implemented in a smartphone application to give end users real-time disease detection in a matter of seconds.

The authors of [149] have proposed an automated DL with a wavelet neural network (ADLWNN) model that focuses on the effective detection and classification of rice plants. To extract features from the input rice plant images, the proposed ADLWNN model principally employed a CNN model. Furthermore, the manta ray optimization algorithm (MRFO) was used as a hyperparameter optimizer. Furthermore, the WNN model was used for the accurate detection and classification of rice plant images. The simulation analysis of the ADLWNN model was tested using a set of rice plant images, and the findings showed that the ADLWNN model outperformed other methodologies by 98.17%.

The authors of [150] have provided a fully automated coffee leaf disease detection framework based on a modified color process in which the syndrome is self-clustered using an extended Gaussian kernel density estimate and the likelihood of the nearest common neighborhood. Accordingly, the proposed extended Gaussian kernel, which joins nearby lesions in one symptom cluster without the necessity for any influencing set that guides towards the correct cluster, yielded the best probabilities. Clusters are provided with the same priority as a kernel density estimation (KDE) with the ResNet50 classifier, reducing misclassification with an accuracy of up to 98%. To identify plant diseases, residual attention learning has been proposed. The work makes use of four different datasets [151] the residual attention network (Res-ATTEN) is used to compute attention-aware characteristics in the system. The proposed technique has reached state-of-the-art performance, with 99% for apples and rice, 94% for corn, and 97% for grapes.

The DeepPlantNet DL-based architecture has been proposed, and the study was efficient, unique, and lightweight for predicting and categorizing plant leaf diseases [152]. The DeepPlantNet model suggested consists of 28 learned layers, 25 convolutional layers (ConV), and three fully connected (FC) layers. It was a unique plant disease classification system that used Leaky RelU (LReLU), batch normalization (BN), fire modules, and a mix of 33 and 11 filters. The proposed DeepPlantNet model can classify plant disease photos into a variety of categories. The proposed method divides plant diseases into the ten categories listed below: peach_bacterial_spot (PBS), pepper_bell_bacterial_spot (PBBS), potato_early_blight (PEB), squash_powdery_mildew (SPM), strawberry_leaf_scorch (SLS), bacterial tomato spot (TBS), and maize common rust (MCR). In the case of eight-class and three-class classification schemes, the proposed framework attained average accuracy of 98.49 and 99.85, respectively. The authors of [153] have proposed a PDD framework (i.e., PDD-Net) based on CNN, which leverages data augmentation techniques and includes multilevel and multiscale features to produce a class and scale-invariant architecture. The flatten-t swish (FTS) activation function was used to prevent gradient disappearing and explosion difficulties during PDD-Net training, while the focused loss function was used to alleviate the impact of class imbalance. On the PlantVillage dataset, the PDD-Net technique beats baseline models, attaining an average precision of 92.06%, recall of 92.71%, F1 score of 92.36%, and accuracy of 93.79%. On the cassava leaf disease dataset, it achieves an average precision of 86.41%, recall of 85.77%, F1 score of 86.02%, and accuracy of 86.98%. These findings indicate PDD-Net's efficiency and resilience in plant disease diagnosis.

Early detection of plant diseases is critical because they inflict social, ecological, and economic costs [154]. In this study, four well-known CNN models (MobileNetV3Small, EfficientNetV2L, InceptionV3, and MobileNetV2) are used in addition to the suggested two novel CNN models. The experimental results show that the suggested ensemble models stand out for their quick training and testing times, as well as their excellent classification performances with a 99.60% accuracy.

The authors of [155] have proposed a DNSVM classification technique that combines DenseNet-201 with SVM to identify plant leaf diseases. The PlantVillage dataset had good variations, color differences, differences in orientation, and leaf size. Sugarcane plant leaves were employed for the suggested model's performance examination, and it achieved 97.78% classification accuracy above the previous DenseNet-121-based classifier model (94%).

The authors of [156] have suggested two DL techniques for palm leaf disease classification: residual network (ResNet) and inception ResNet TL. The models enable the training of hundreds of layers while achieving excellent performance. Given the value of their excellent representation ability, the performance of image classification using ResNet has improved, such as in the disease classification of plant leaves. Both approaches addressed issues such as brightness and backdrop variance, image scale variation, and inter-class similarity. The date palm dataset, which included 2,631 colored images of varying sizes, was utilized to train and test the models. Using certain well-known measures, the suggested models surpassed many prior studies in the field in both original and augmented datasets, achieving an accuracy of 99.62% and 100%, respectively.

Table 1 summarizes the DL and ML-based implemented plant leaf and/or crop species disease detection and classification research works including the type (s) of plant, used techniques/models/algorithms, and accuracies.

Performance evaluation of plant disease detection and classification

Since agriculture is a significant part of the population around the globe, a comprehensive research study on several types of DL and ML approaches for different plant leaf and/or crop disease detection and classification has been implemented. Following that, different classification techniques in the DL and ML approaches may be utilized for plant disease detection and classification, to assist farmers with automatic disease detection and classification of all types of disease in the crop that were to be identified [162].

The distribution of relevant papers over the years has been depicted in Fig. 5. The Figure shows an increase in plant leaf and/or crop disease detection and classification over the years.

Accurately detecting and classifying different plant disease occurrence at an early stage is critical for crop quality and result through the selection of appropriate treatments [150, 163]. The detection of such diseases on a large scale in a timely and accurate way is prone to human error [164, 165]. Accordingly, ML and DL techniques offer possibilities for developing automated models that can detect such diseases promptly. However, disease identification and classification necessitate specialized knowledge and extensive experience in plant pathology. Thus, by developing an early detection and classification system for disease, an automated system for disease detection in crops will play an essential role in agricultural industries. Automatic plant disease detection and classification is an interesting study area since it may be useful for monitoring enormous fields and, hence, the automatic identification and classification of disease by symptoms in different plant sections [166]. Image dataset size, class numbers, preprocessing techniques, classification approaches, performance analysis, and so on are examples of these measurements. The previous decade's research was thoroughly reviewed, including studies on several plant diseases, and an investigation of the important features was provided. This work contributes by comparing the automated detection and classification of various plant diseases through the use of image processing, DL, ML, and meta-heuristic optimization techniques. The study gives information on many methods used to identify diseases in various plants. The study's various elements include the type of segmentation, dividing technology, extracted features, dataset size and year of publication, disease category, methodologies, detection accuracy, classification, and constraints accordingly.

Evaluation metrics

The application of DL approaches to detect and classify plant diseases can avoid the disadvantages of artificial selection of disease spot features, making plant disease feature extraction more objective, and increasing research performances and technology transformation speed [167]. The researchers in the literature have measured their proposed

Table 1 Summary of the related works using the DL and ML techniques

Author(s)	Type(s) of plant	Used model(s)/Algorithms/Technique(s)	Accuracy %
[1]	✓ Soybean	✓ YoloV5 ✓ InceptionV3 ✓ CNN	✓ 98.75 ✓ 97.00 ✓ 97.00
[3]	✓ Banana	✓ CNN	✓ 93.45
[4]	✓ Rice	✓ ResNet 50 ✓ ResNet101 ✓ DenseNet161 ✓ DenseNet169	✓ 91.68 ✓ 92.50 ✓ 95.74 ✓ 94.98
[5]	✓ Tomato	✓ PCA, Linear SVM	✓ 88.67
[6]	✓ Potato ✓ Tomato ✓ Strawberry ✓ Corn ✓ Grape ✓ Apple	✓ LR ✓ KNN ✓ CNN ✓ SVM	✓ 66.4 ✓ 54.5 ✓ 53.4 ✓ 98.0
[7]	✓ Apple ✓ Corn ✓ Grapes ✓ Potato ✓ Sugarcane ✓ Tomato	✓ CNN	✓ 96.5
[8]	✓ Tomato	✓ CNN and LQV	✓ 86.00
[9]	✓ Rice	✓ InceptionResNetV2 ✓ Xception ✓ ResNet50 ✓ MobileNet ✓ InceptionV3	✓ 98.9 ✓ 97.65 ✓ 97.00 ✓ 96.65 ✓ 95.85
[12]	✓ Turmeric	✓ VGG-16	✓ 96.24
[13]	✓ Different plant leaf species	✓ SVM	✓ 92.4
[14]	✓ Tomato ✓ Pepper ✓ Potato	✓ CNN	✓ 98.029 (for testing) ✓ 98.29 (for training)
[25]	✓ Rice	✓ DCNN	✓ 99.7
[26]	✓ Tomato	✓ CNN	✓ 99.64
[29]	✓ Rice ✓ Apple ✓ Bean ✓ Potato ✓ Tomato	✓ DenseNet-121	✓ 98.00 ✓ 96.00 ✓ 94.00 ✓ 95.00 ✓ 97.00
[33]	✓ Tomato	✓ AlexNet with TL ✓ AlexNet with FE	✓ 89.69 with an 80/20 and 88.45% with a 70/30 ratios ✓ 93.4 with an 80/20 and 92.11% with a 70/30 ratios
[39]	✓ Rice	✓ TL ✓ CNN + TL ✓ ANN ✓ ECNN + GA	✓ 80.00 ✓ 85.00 ✓ 90.00 ✓ 95.00
[40]	✓ Different plant leaf species	✓ LR ✓ SVM ✓ KNN ✓ RF ✓ NB ✓ CNN	✓ 71.89 ✓ 75.76 ✓ 82.17 ✓ 97.12 ✓ 81.12 ✓ 98.43
[41]	✓ Rice	✓ DenseNet169 ✓ Xception (fine-tuned TL)	✓ 99.66 ✓ 99.99
[42]	✓ Different plant leaf species	✓ C-GAN ✓ CNN ✓ SGD ✓ ACO-CNN	✓ 99.6 ✓ 99.97 ✓ 85.00 ✓ 99.98

Table 1 (continued)

Author(s)	Type(s) of plant	Used model(s)/Algorithms/ Technique(s)	Accuracy %
[43]	✓ Different plant leaf species	✓ EfficientB5Net ✓ InceptionV3Net ✓ DenseNet201 ✓ AlexNet ✓ ResNet152 ✓ VGG19Net ✓ PPLC-Net	✓ 94.512 ✓ 96.347 ✓ 95.481 ✓ 89.548 ✓ 95.728 ✓ 92.695 ✓ 99.702
[44]	✓ Tomato	✓ 2-DCNN	✓ 96.00
[45]	✓ Apple ✓ Corn ✓ Cotton ✓ Grape ✓ Pepper ✓ Rice	✓ Dilated TL and EL	✓ 99.10
[46]	✓ Lemon ✓ Banana ✓ Beans ✓ Rose	✓ SVM with the proposed algorithm	✓ 95.71
[47]	✓ Tomato	✓ EL based DL	✓ 96.00
[48]	✓ Tomato	✓ ResNet50-CBAM + SVM	✓ 97.20
[49]	✓ Tomato	✓ Faster-RCNN (RESNET-34)	✓ 99.97
[51]	✓ Ginger	✓ CNN	✓ 95.2
[52]	✓ Different plant leaf species	✓ DCNN with YOLOv7	✓ 99.50
[53]	✓ Cotton	✓ CNN	✓ 100 and 90 for identification and classification respectively
[54]	✓ Coffee	✓ DT with BPNN	✓ 94.5
[55]	✓ Tomato	✓ GAR	✓ 96.70
[56]	✓ Tomato	✓ Customized U-Net	✓ 98.12
[57]	✓ Coffee	✓ TL through Mobilnet ✓ Resnet50	✓ 97.01 ✓ 99.89
[58]	✓ Tomato	✓ U-Net and Modified U-Net	✓ 99.97 (binary class) ✓ 99.22 (Multi-Class (6)) ✓ 99.91 (Multi-Class (10))
[59]	✓ Tomato	✓ KNN ✓ SVM	✓ 99.92 ✓ 99.90
[60]	✓ Olive	✓ MobiRes-Net ✓ ResNet50 ✓ MobileNet	✓ 97.08 ✓ 94.86 ✓ 95.63
[61]	✓ Rice	✓ PlantDet	✓ 98.53
[62]	✓ Different plant leaf species	✓ DenseNet-77	✓ 99.98
[63]	✓ Tomato	✓ DCNN	✓ 98.49
[64]	✓ Tomato	✓ A multinomial LR	✓ 97.00
[65]	✓ Canola ✓ Corn ✓ Wild radish	✓ K-FLBPCM	✓ 98.63
[66]	✓ Tea	✓ GLCM with Harris ✓ and SVM	✓ 97.48
[67]	✓ Turmeric	✓ KMC, GLCM, GLCM, and SVM	✓ 91.61
[68]	✓ Tomato	✓ CNN	✓ 94.00
[69]	✓ Maize	✓ SVM ✓ NB ✓ KNN ✓ DT ✓ RF	✓ 77.56 ✓ 77.46 ✓ 76.16 ✓ 74.35 ✓ 79.23
[70]	✓ Rice	✓ TL (InceptionV3, MobileNetV2 and DenseNet121)	✓ 96.42

Table 1 (continued)

Author(s)	Type(s) of plant	Used model(s)/Algorithms/ Technique(s)	Accuracy %
[71]	✓ Tomato	✓ ResNet101,VGG16,VGG19,GoogleNet, AlexNet, ResNet50	✓ 94.6
[72]	✓ Tomato	✓ MobileNetV2	✓ 99.30
[73]	✓ Apple ✓ Blueberry ✓ Cherry ✓ Corn ✓ Grape ✓ Orange ✓ Peach ✓ Pepper bell ✓ Potato ✓ Raspberry ✓ Soybean ✓ Squash ✓ Strawberry ✓ Tomato	✓ InceptionV3 ✓ InceptionResnetV2 ✓ MobileNetV2 ✓ EfficientNetB0	✓ 98.42 ✓ 99.11 ✓ 97.02 ✓ 99.56
[74]	✓ Tomato	✓ SE-ResNet50	✓ 96.81
[75]	✓ Tomato	✓ OpenCV	✓ 98.00
[76]	✓ Tomato	✓ DNN	✓ 86.18
[77]	✓ Tomato	✓ GoogleNet, AlexNet, Inception V3,ResNet 18,ResNet 50	✓ 99.72
[78]	✓ Tomato	✓ AlexNet	✓ 76.1
[79]	✓ Tomato	✓ MobileNet V2	✓ 90.00
[80]	✓ Tomato	✓ Hybrid SVM	✓ 92.37
[81]	✓ Apple ✓ Blueberry ✓ Cherry ✓ Corn ✓ Grape ✓ Orange ✓ Peach ✓ Pepper ✓ Potato ✓ Raspberry ✓ Soybean ✓ Squash ✓ Strawberry ✓ Tomato	✓ DCNN	✓ 96.46
[82]	✓ Tomato	✓ Multiclass SVM	✓ 94.00
[83]	✓ Tomato	✓ TL based DCNN	✓ 99.55
[84]	✓ Tomato	✓ VGG16 ✓ InceptionV3 ✓ MobileNet	✓ 91.2 ✓ 63.40 ✓ 63.75
[85]	✓ Tomato	✓ CNN in PlantVillage dataset ✓ CNN other than the PlantVillage dataset ✓ A traditional ML with *KNN* ✓ VGG16	✓ 98.4 ✓ 98.7 ✓ 94.9 ✓ 93.5
[87]	✓ Citrus	✓ GLCM, k-means, SVM	✓ 90.00
[90]	✓ Rice	✓ Vgg16 ✓ Vgg19 ✓ ResNet50 ✓ ResNet50v2 ✓ ResNet101v2	✓ 70.42 ✓ 73.60 ✓ 51.99 ✓ 61.60 ✓ 86.79
[91]	✓ Rice	✓ SVM, DCNN	✓ 97.5
[93]	✓ Grape	✓ KMC and SVM	✓ 88.89
[94]	✓ Soybean	✓ SIFT and SVM	✓ 93.79

Table 1 (continued)

Author(s)	Type(s) of plant	Used model(s)/Algorithms/ Technique(s)	Accuracy %
[95]	✓ Maize ✓ Grape ✓ Apple ✓ Tomato	✓ MobileNet50 ✓ PDDNN	✓ 74.90 ✓ 86.00
[96]	✓ Cotton	✓ DCNN	✓ 96.00
[98]	✓ Tomato	✓ AlexNet ✓ SqueezeNet	✓ 95.65 ✓ 94.30
[99]	✓ Tomato	✓ CNN	✓ 97.00
[105]	✓ Rice	✓ CNN	✓ 92.46
[110]	✓ Guava	✓ DCNN	✓ 98.74
[112]	✓ Apple ✓ Blueberry ✓ Cherry ✓ Corn ✓ Grape ✓ Orange ✓ Peach ✓ Pepper bell ✓ Potato ✓ Raspberry ✓ Soybean ✓ Squash ✓ Strawberry ✓ Tomato	✓ CNN	✓ 99.35
[113]	✓ Cotton	✓ ANN	✓ 80.00
[114]	✓ Different plant leaf species	✓ ANN	✓ 92.00
[119]	✓ Groundnut	✓ Back propagation	✓ 97.00
[121]	✓ Phyllanthus Elegans	✓ MLP ✓ RBF	✓ 90.15 ✓ 98.85
[122]	✓ Cotton ✓ Soybeans	✓ ANN	✓ 83.00 ✓ 80.00
[123]	✓ Potato ✓ Tomato ✓ Pepper bell	✓ CNN, Bayesian algorithm	✓ 98.90
[124]	✓ Grapes	✓ Hybrid CNN	✓ 98.70
[125]	✓ Strawberry	✓ FL	✓ 96.00
[126]	✓ Apple	✓ PR	✓ 90.00
[128]	✓ Maize	✓ CNN	✓ 96.76
[132]	✓ Different plant leaf species	✓ NB	✓ 97.00
[134]	✓ Rice ✓ Potato	✓ CNN	✓ 99.58 ✓ 97.66
[136]	✓ Guava	✓ CNN	✓ 95.61
[137]	✓ Potato	✓ KMC and GLCM	✓ 95.99
[138]	✓ Beans	✓ MobileNet	✓ 92.00
[139]	✓ Maize	✓ GoogleNet ✓ Cifa10	✓ 98.90 ✓ 98.80
[140]	✓ Onion	✓ DCNN	✓ 85.47
[142]	✓ Rice	✓ ADSNN-BO	✓ 94.65
[143]	✓ Tomato	✓ RF	✓ 95.00
[144]	✓ Different plant leaf species	✓ KMC and CNN	✓ 92.60
[145]	✓ Sugarcane	✓ SVM	✓ 95.00
[146]	✓ Cassava	✓ ANN and KNN	✓ 90.00

Table 1 (continued)

Author(s)	Type(s) of plant	Used model(s)/Algorithms/ Technique(s)	Accuracy %
[147]	✓ Tomato ✓ Potato ✓ Rice ✓ Pepper bell	✓ ML and DL	✓ 99.4 for binary class ✓ 99.2 for multiclass
[148]	✓ Maize	✓ YOLOv3-tiny ✓ YOLOv4 ✓ YOLOv5s ✓ YOLOv7s ✓ YOLOv8n	✓ 69.40 ✓ 97.50 ✓ 88.23 ✓ 93.30 ✓ 99.04
[149]	✓ Rice	✓ ADLWNN	✓ 98.17
[150]	✓ Cofee	✓ KDE + ResNet50	✓ 98.00
[151]	✓ Apple ✓ Rice ✓ Corn ✓ Grape	✓ Res-ATTEN	✓ 99.00 ✓ 99.00 ✓ 94.00 ✓ 97.00
[152]	✓ Maiz ✓ Potato ✓ Tomato	✓ DeepPlantNe DL	✓ 98.49 (in eight classes) and 99.85 (in three classes)
[153]	✓ Apple ✓ Maize ✓ Cherry ✓ Corn/Maze ✓ Grape ✓ Peach ✓ Potato ✓ Cassava	✓ PDD-Net	✓ 93.79 (in PlantVillege dataset) ✓ 86.98 (only for Casava)
[154]	✓ Tomato	✓ CNN	✓ 99.60
[155]	✓ Sugarcane	✓ DNSVM	✓ 97.78
[156]	✓ Palm	✓ ResNet	✓ 99.62 (for the original dataset) and 100% (for the augmented dataset)
[157]	✓ Maize	✓ RF	✓ 80.68
[158]	✓ Mini-leaves ✓ Sugarcane	✓ SSM-Net	✓ 92.7 ✓ 94.30
[159]	✓ Vegetables	✓ KMC	✓ 95.16
[160]	✓ Weed	✓ Histogram analysis ✓ SIFT	95.00 ✓ 99.00
[161]	✓ Rice	✓ TL	✓ 99.64

techniques by using different performance evaluation metrics such as accuracy, mean average precision (mAP), recall, precision, Intersection over Union (IoU), sensitivity, and specificity [62]. Equations (1), (2), (3), (4), (5), (6), (7), and (8) are defined and describe how to evaluate the performances of the plant disease detection and classification techniques.

A. Accuracy The accuracy score of a model, often known as accuracy, is a classification statistic in DL and ML techniques that represents the proportion of correct predictions made by the model.

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

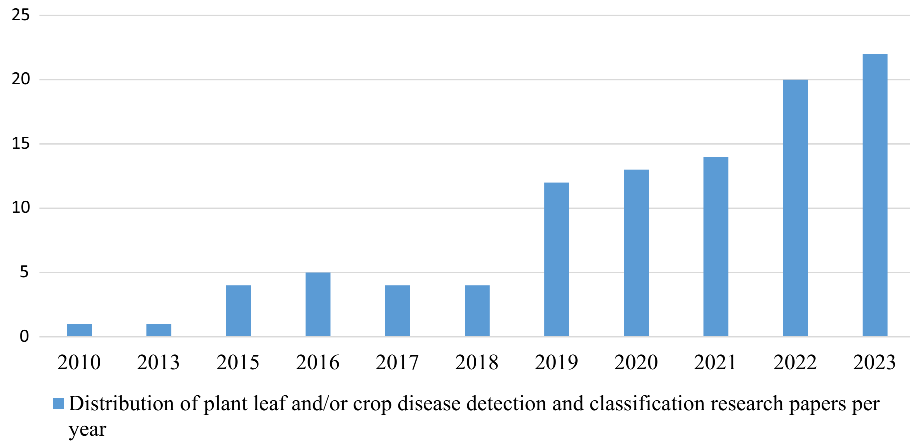

Fig. 5 Distribution of plant leaf and/or crop disease detection and classification research papers per year (i.e., for this particular study)

B. mAP When the Intersection over Union (IOU) is greater than or equal to the threshold, mAP is the accuracy. It is the ratio of a true and predicted region of interests' intersection area to the union of the same. At different thresholds, detection performance is measured in thresholds of mAP.

$$mAP = \sum_{i=1}^{T} \frac{AP(\mathrm{Ti})}{T} \tag{2}$$

where AP denotes the average precision of each class and q is the query or test image. Q is the total number of test images:

C. Recall A model's recall is defined as the model's ability to correctly identify True Positives. It is defined as the ratio of correctly classified positive outputs to correctly classified outputs.

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

D Precision Precision is defined as the ability to identify only relevant objects. It is defined as the ratio of correctly classified positive outputs to total positive outputs.

$$Precision = \frac{TP}{(TP + FP)} \tag{4}$$

E. F1-score The f1 score is also introduced to assess the model's accuracy. The f1-score considers both the model's precision and recall [34].

$$F1 - score = 2 * (Precision * \frac{2(*Precision * Recall)}{(Precision + Recall)} * 100\% \tag{5}$$

F. intersection over union (IoU)

$$IoU = \frac{TP}{(FN + FP + TP)} * 2 \tag{6}$$

G. Sensitivity

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{7}$$

H. Specificity

$$Specificity = \frac{TN}{(TN + FP)} \tag{8}$$

where TP, TN, FP, and FN are for True Positive, True Negative, False Positive, and False Negative respectively.

In addition to the above performance evaluation metrics, determining the performances of the plant leaf and /or crop disease detection and classification performance should be evaluated in terms of the Logarithmic Loss (including the training loss, validation loss, and testing loss) and Area Under Curve (AUC) metrics accordingly. As indicated in [62], designing an effective logarithmic loss function is mandatory for the robust performance of plant leaf and /or crop disease detection and classification models.

Results and discussions

A comparative review of different research works done in different plant leaf disease detection and classification using DL and ML techniques has been investigated by many researchers. Accordingly, when sufficient data is available for training, DL techniques are capable of detecting and classifying plant leaf diseases with high accuracy. As indicated in Figs. 6, 7, 8, and 9, different researchers have developed plant leave disease detection and classification systems by using plant leave images. Here, most of the researchers have tested their proposed systems on different plant leaves. They have computed the evaluation metrics such as accuracy, precision, recall, f1-score, mAP, IoU, sensitivity, specificity, and Matthews correlation coefficient (MCC) for training and testing purposes. Accordingly, for this particular comparative study, the author has considered only

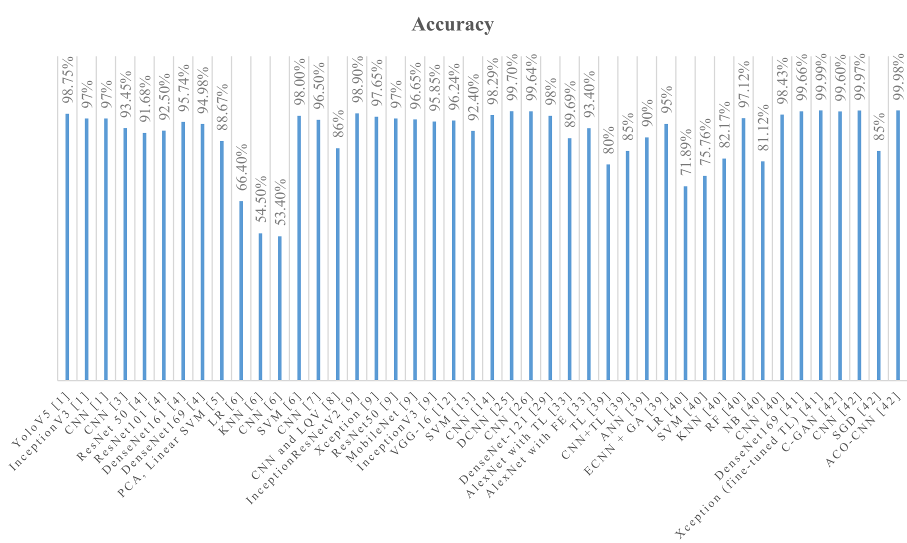

Fig. 6 Performances of the DL and ML techniques in the study **a**

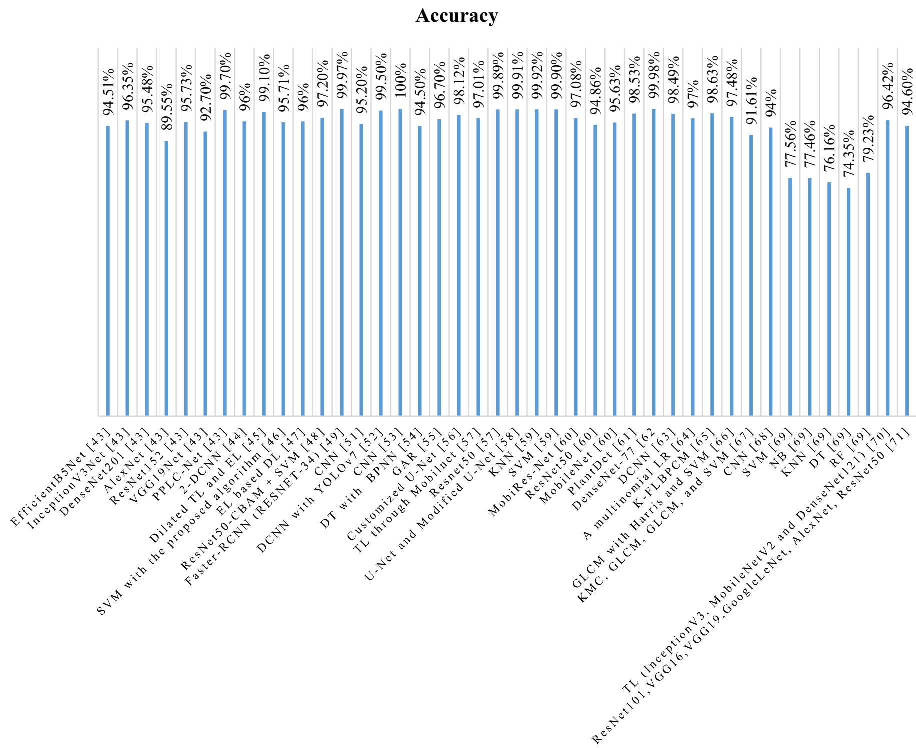

Fig. 7 Performances of the DL and ML techniques in the study **b**

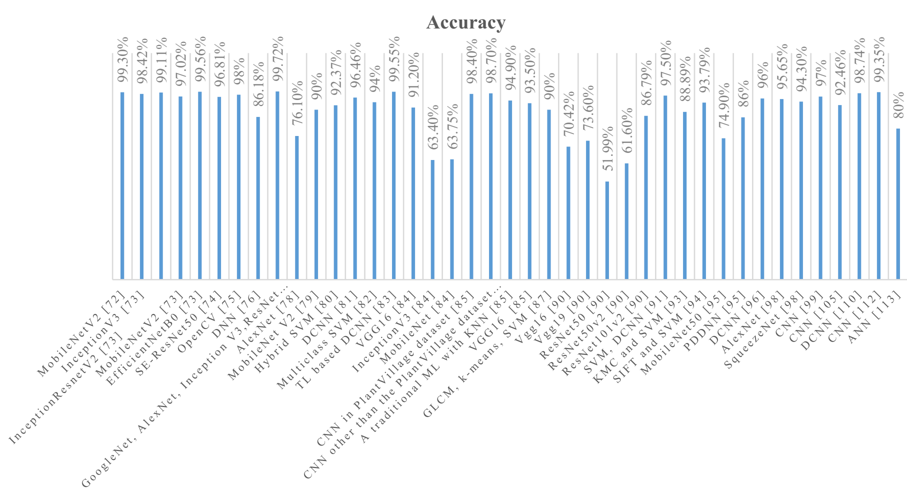

Fig. 8 Performances of the DL and ML techniques in the study **c**

the accuracy of the literature. Additionally, the maximum accuracy (including multiclass level accuracies accordingly) result has been considered in plant leaf disease detection and classification research work that has been tested on different plant leaves in the literature.

As depicted in Figs. 6, 7, 8, and 9, CNNs are generally superior to SVMs for plant leaf disease detection and classification tasks by using the images of plants accordingly.

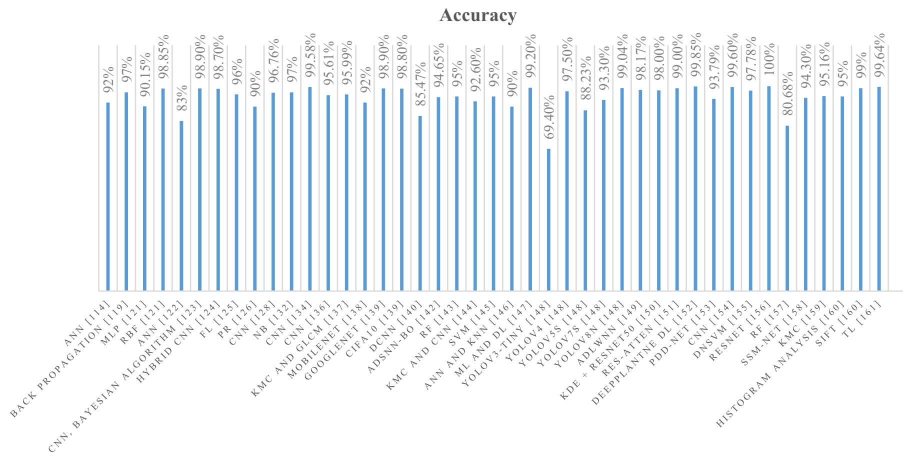

Fig. 9 Performances of the DL and ML techniques in the study **d**

CNNs are specifically designed for handling image data, as they can automatically learn hierarchical features from raw pixel values. They use convolutional layers to capture local patterns and hierarchical representations, enabling them to excel at tasks like object recognition, image detection, and classification. DL and ML both have roles in image detection and classification. ML techniques like SVMs may be sufficient for simple image detection and classification tasks with well-defined features. However, DL, including CNNs, is typically more powerful and versatile for complex image tasks. DL models can automatically learn intricate features and representations, reducing the need for manual feature engineering. Hence, for most modern image detection classification tasks, DL, particularly CNNs, is the preferred choice due to their ability to outperform traditional ML techniques in terms of accuracy and efficiency [161].

CNNs are often the favored choice for image detection and classification due to their inherent capacity to autonomously acquire pertinent image features and grasp spatial hierarchies. Nevertheless, the selection between conventional ML and DL hinges on the particular problem, the accessibility of data, and the computational capabilities accessible. In numerous advanced image detection and classification tasks, DL, mainly through CNNs, is preferred when ample data and computational resources are available.

The significance of collecting large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving detection and classification accuracies, as well as the significance of small sample plant leaf disease detection, classification, and hyper-spectral imaging for early detection and classification of plant disease, have all been mandatory activities to increase the best results of agricultural products [62]. Most of the DL frameworks proposed in the study showed good detection and classification effects on their datasets but not on other datasets, indicating that the model is not good. As a result, more robust DL models are required to adapt to the different disease datasets. The PlantVillage dataset was used to evaluate the performance of both DL and ML techniques in most of the studies. Although the dataset contains several images of various plant species with diseases, they were all taken in the lab. As a result, a large dataset of plant diseases in real-world situations is expected. Although some researchers use hyperspectral images of diseased leaves and different

DL and ML frameworks for the early detection and classification of plant leaf diseases, issues that affect the widespread use of hyperspectral imaging (HSI) in the early detection and classification of plant diseases have yet to be resolved [168]. That is, it is difficult to get labeled datasets for early plant disease detection and classification, and even experienced experts cannot mark where the invisible disease symptoms are and define purely invisible disease pixels, which is critical for HSI to detect plant disease. The analysis of the reviewed papers revealed that the detection and classification of plant disease is a hot issue and needs further investigation. The detection and classification of plant leaf disease for different crops are a pressing issue and a complex process, partly due to the availability of datasets and the task of developing an ML model with rigid performance.

As depicted in Figs. 6, 7, 8, and 9 below, based on the reviewed research works in the area, most researchers have achieved better evaluation results with the DL technique than with the ML technique for developing plant disease detection and classification systems. Additionally, most researchers have combined different techniques, such as DL and ML, to detect and classify various plant leaves. Accordingly, though SVM has excellent performance in image detection and classification, its performance depends on the image features it receives. It is suggested to combine CNN features with the SVM classifier unless the researchers plan to use pre-trained models.

As depicted in Fig. 10, most of the studies that have been included in this particular study have concentrated on the detection and classification of different diseases in tomato and rice crops, respectively. In addition to the tomato and rice crops, the researchers have tried to conduct disease detection and classification studies on different plant leaves and/or crop species accordingly.

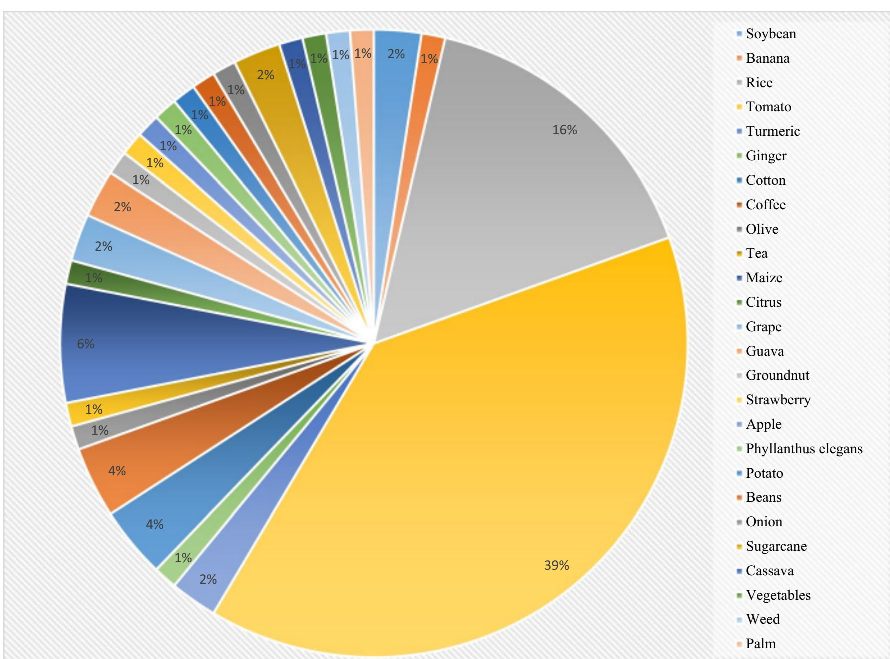

Fig. 10 Distribution of the studies per plant leaf and/or crop species (i.e., for this particular study)

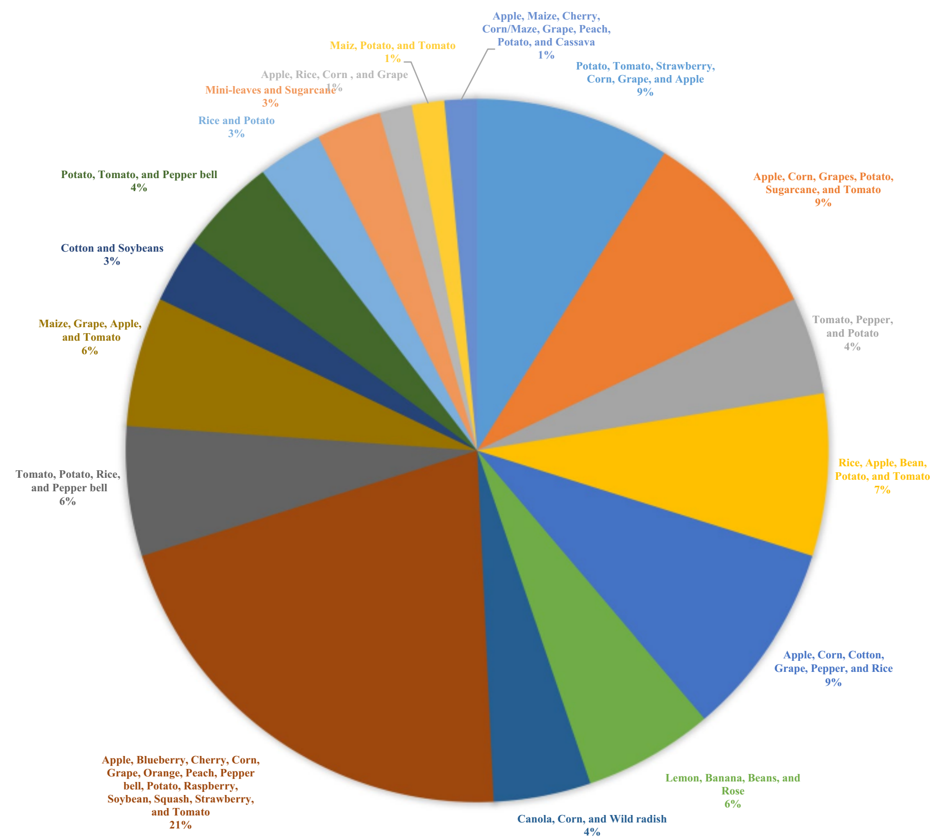

Fig. 11 Distribution of the studies per multiple plant leaf and/or crop species

Currently, plant leaf and/or crop species disease detection and classification studies have been implemented and tested using different techniques and approaches for multiple plant leaf and/or crop species accordingly. As summarized in Fig. 11, plant leaf and/or crop species disease detection and classification techniques and approaches have been implemented for more than two plants. From Fig. 11, the Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper Bell, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato plant leaf and/or crop species have been implemented and tested by the CNN technique and achieved an overall accuracy of 99.35%.

Additionally, most of the researchers have tried to include the tomato plant in the selected plant leaf and/or crop species disease detection and classification research works. This indicates that the tomato plant is the most researchable plant leaf and/or crop species.

Conclusion and recommendation

The literature provided many strategies that have been developed and made available to aid in the achievement of enormous accomplishments in the fields of ML, DL, and image processing. The assessment also stated that the percentage accuracy can be enhanced by training and testing the models with more and more datasets to boost the classification and identification accuracy. To address the problem of plant leaf or crop disease, new and better DL algorithms that can provide higher accuracy in identifying and classifying plant leaf or crop diseases must always be developed and applied.

Several methods for classifying plant leaf diseases have been developed and used in the past. However, neural networks, such as CNN, appear to be the ideal technique for classifying plant diseases due to their flexibility and feature extractor property, which allows them to extract features automatically. Unlike prior models such as NB, KNN, SVM, RFC, and others, CNN may learn extra features from images to produce superior results. Because of their sophistication in learning and extracting information from images for trustworthy output, neural networks such as CNN are well suited for research work in the areas of computer vision and image processing. In addition, from the DL and ML techniques that have been included in this particular study, CNNs are often the favored choice for image detection and classification due to their inherent capacity to autonomously acquire pertinent image features and grasp spatial hierarchies. Nevertheless, the selection between conventional ML and DL hinges upon the particular problem, the accessibility of data, and the computational capabilities accessible. Accordingly, in numerous advanced image detection and classification tasks, DL, mainly through CNNs, is preferred when ample data and computational resources are available and show good detection and classification effects on their datasets, but not on other datasets.

Finally, the author recommends future researchers to investigate plant disease detection and classification research works by considering the following points accordingly:

- Developing DL models for disease detection and classification in different parts of plants.
- To improve the robustness of homemade datasets in complicated contexts, an automated parameter search technique for the weather data augmentation method should be developed.
- Data augmentation, large datasets with significant variability, and other strategies can increase plant disease detection and classification accuracies.
- Expanding the recommended techniques will result in a significant contribution to sustainable agriculture, influencing crop quality for future generations.
- Using preprocessing techniques on the dataset, such as resizing and augmentation.
- DL models for real-time disease detection are being developed.
- Development of an Android app that detects the presence of diseases on different plants using a DL model.
- Develop such plant leave detection and classification systems by combining DL and ML techniques such as DCCN and CNN features with SVM techniques.

Acknowledgements

I want to thank all the researchers who have been cited (included) in this particular research work.

Author contributions

WBD: Prepared manuscript including analysis, data curation, visualization, conceptualization, methodology, and writing of the original draft.

Funding
This study did not receive any funds.

Availability of data and materials
The research data are available from the authors and can be accessed from the author accordingly.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The author declares that no competing interest.

Received: 10 September 2023 Accepted: 14 December 2023
Published online: 02 January 2024

References

1. Tirkey D, Singh KK, Tripathi S. Performance analysis of AI-based solutions for crop disease identification detection, and classification. Smart Agric Technol. 2023. https://doi.org/10.1016/j.atech.2023.100238.
2. Ramanjot, et al. Plant disease detection and classification: a systematic literature review". Sensors. 2023. https://doi.org/10.3390/s23104769.
3. Krishnan VG, Deepa J, Rao PV, Divya V, Kaviarasan S. An automated segmentation and classification model for banana leaf disease detection. J Appl Biol Biotechnol. 2022;10(1):213–20. https://doi.org/10.7324/JABB.2021.100126.
4. S Mathulaprangsan K Lanthong S Patarapuwadol. 2020. Rice Diseases Recognition Using Effective Deep Learning Models. Telecommun. Eng Media Technol with ECTI North Sect Conf Electr Electron Jt Int Conf Digit Arts Comput. https://doi.org/10.1109/ECTIDAMTNCON48261.2020.9090709
5. Heltin Genitha C, Dhinesh E, Jagan A. Detection of leaf disease using principal component analysis and linear support vector machine. Adv Comput ICoAC Proc Int Conf. 2019. https://doi.org/10.1109/ICoAC48765.2019.246866.
6. P. S. Gupta, P. Hans, and S. Chand. 2020. Classification Of Plant Leaf Diseases Using Machine Learning And Image Preprocessing Techniques.
7. S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conf. IOT, Commun. Eng., pp. 579–582, 2019.
8. Sardogan M, Tuncer A, Ozen Y. Plant leaf disease detection and classification based on CNN with LVQ algorithm. Comput Sci Eng Conf. 2018. https://doi.org/10.1109/UBMK.2018.8566635.
9. Sharma M, Kumar CJ, Deka A. Early diagnosis of rice plant disease using machine learning techniques. Arch Phytopathol Plant Prot. 2022;55(3):259–83. https://doi.org/10.1080/03235408.2021.2015866.
10. Sharath DM, Akhilesh S, Kumar A, Rohan MG, Prathap C. Image based plant disease detection in pomegranate plant for bacterial blight. Proc IEEE Int Conf Commun Signal Process ICCSP. 2019. https://doi.org/10.1109/ICCSP.2019.8698007.
11. Kumar S, Raghavendra BK. Diseases detection of various plant leaf using image processing techniques: a review" 2019 5th. Comput Commun Int Conf Adv. 2019. https://doi.org/10.1109/ICACCS.2019.8728325.
12. Rajasekaran C, Arul S, Devi S, Gowtham G, Jeyaram S. Turmeric plant diseases detection and classification using artificial intelligence. Int Conf Signal Process Commun. 2020. https://doi.org/10.1109/ICCSP48568.2020.9182255.
13. P. V., R. Das, and K. V. Identification of plant leaf diseases using image processing techniques. 2017 IEEE Int. Conf. Technol. Innov. ICT Agric. Rural Dev. (TIAR 2017), pp. 130–133, 2017.
14. Jasim MA, Al-Tuwaijari JM. Plant leaf diseases detection and classification using image processing and deep learning techniques. Int Comput Sci Soft Eng Conf. 2020. https://doi.org/10.1109/CSASE48920.2020.9142097.
15. Bedi P, Gole P. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. Artif Intell Agric. 2021;5:90–101. https://doi.org/10.1016/j.aiia.2021.05.002.
16. Uchida S, Ide S, Iwana BK, Zhu A. A further step to perfect accuracy by training CNN with larger data. Int Conf Front Handwrit Recognit. 2016. https://doi.org/10.1109/ICFHR.2016.0082.
17. Hu Y, Liu G, Chen Z, Liu J, Guo J. Lightweight one-stage maize leaf disease detection model with knowledge distillation. Agriculture. 2023;13:1–22.
18. Ma L, Yu Q, Yu H, Zhang J. Maize leaf disease identification based on yolov5n algorithm incorporating attention mechanism. Agronomy. 2023. https://doi.org/10.3390/agronomy13020521.
19. Kumar R, Chug A, Singh AP, Singh D. A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a Review. J Sensors. 2022. https://doi.org/10.1155/2022/3287561.
20. Saleem MH, Potgieter J, Arif KM. Plant disease classification: a comparative evaluation of convolutional neural networks and deep learning optimizers. Plants. 2020;9(10):1–17. https://doi.org/10.3390/plants9101319.
21. Tiwari V, Joshi RC, Dutta MK. Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. Ecol Inform. 2021;63: 101289. https://doi.org/10.1016/j.ecoinf.2021.101289.
22. Vishnoi VK, Kumar K, Kumar B. Plant disease detection using computational intelligence and image processing. Berlin Heidelberg: Springer; 2021.

23. Faizal Azizi MM, Lau HY. Advanced diagnostic approaches developed for the global menace of rice diseases: a review. Can J Plant Pathol. 2022;44(5):627–51. https://doi.org/10.1080/07060661.2022.2053588.
24. Shoaib M, et al. An advanced deep learning models-based plant disease detection: a review of recent research. Front Plant Sci. 2023;14:1–22. https://doi.org/10.3389/fpls.2023.1158933.
25. Upadhyay SK, Kumar A. A novel approach for rice plant diseases classification with deep convolutional neural network. Int J Inf Technol. 2022;14(1):185–99. https://doi.org/10.1007/s41870-021-00817-5.
26. Guerrero-Ibañez A, Reyes-Muñoz A. Monitoring tomato leaf disease through convolutional neural networks. Electron. 2023;12(1):1–15. https://doi.org/10.3390/electronics12010229.
27. Picon A, Seitz M, Alvarez-Gila A, Mohnke P, Ortiz-Barredo A, Echazarra J. Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions. Comput Electron Agric. 2019;167:105093. https://doi.org/10.1016/j.compag.2019.105093.
28. Barbedo JGA. A review on the main challenges in automatic plant disease identification based on visible range images. Biosyst Eng. 2016;144:52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017.
29. Ahmed I, Yadav PK. A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases. Sustain Oper Comput. 2023;4:96–104. https://doi.org/10.1016/j.susoc.2023.03.001.
30. Dhiman P, Kaur A, Balasaraswathi VR, Gulzar Y, Alwan AA, Hamid Y. Image acquisition, preprocessing and classification of citrus fruit diseases: a systematic literature review. Sustainability. 2023;15(12):9643. https://doi.org/10.3390/su15129643.
31. Ramesh S, Vydeki D. Application of machine learning in detection of blast disease in south indian rice crops. J Phytol. 2019;11:31–7. https://doi.org/10.25081/jp.2019.v11.5476.
32. Kc K, Yin Z, Li D, Wu Z. "Impacts of background removal on convolutional neural networks for plant disease classification in-situ. Agric. 2021. https://doi.org/10.3390/agriculture11090827.
33. Verma S, Chug A, Singh AP. Application of convolutional neural networks for evaluation of disease severity in tomato plant. J Discret Math Sci Cryptogr. 2020;23(1):273–82. https://doi.org/10.1080/09720529.2020.1721890.
34. Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. Plant Methods. 2021;17(1):1–18. https://doi.org/10.1186/s13007-021-00722-9.
35. Wspanialy P, Moussa M. "A detection and severity estimation system for generic diseases of tomato greenhouse plants. Comput Electron Agric. 2020;178:105701. https://doi.org/10.1016/j.compag.2020.105701.
36. Reddy T, Dharmendra G, Rajput S, Kumar MP, Kuruva R. A novel PCA—whale optimization—based deep neural network model for classification of tomato plant diseases using GPU. J Real-Time Image Process. 2021;18(4):1383–96. https://doi.org/10.1007/s11554-020-00987-8.
37. Chen J, Chen J, Zhang D, Nanehkaran YA, Sun Y. A cognitive vision method for the detection of plant disease images. Mach Vis Appl. 2021;32(1):1–18. https://doi.org/10.1007/s00138-020-01150-w.
38. Hossain SMM, Deb K, Dhar PK, Koshiba T. Plant leaf disease recognition using depth-wise separable convolution-based models. Symmetry. 2021;13(3):1–29. https://doi.org/10.3390/sym13030511.
39. Balaji V, et al. Deep transfer learning technique for multimodal disease classification in plant images. Contrast Media Mol Imaging. 2023;2023:5644727. https://doi.org/10.1155/2023/5644727.
40. Kirola M, Joshi K, Chaudhary S, Singh N, Anandaram H, Gupta A. Plants diseases prediction framework: a image-based system using deep learning. Proc IEEE World Conf Appl Intell Comput. 2022. https://doi.org/10.1109/AIC55036.2022.9848899.
41. S. C. Gopi and H. K. Kondaveeti. Transfer learning for rice leaf disease detection. 2023. https://doi.org/10.1109/ICAIS56108.2023.10073711.
42. Algani YMA, Caro OJM, Bravo LMR, Kaur C, Al Ansari MS, Bala BK. Leaf disease identification and classification using optimized deep learning. Meas Sensors. 2023;25:100643. https://doi.org/10.1016/j.measen.2022.100643.
43. Dai G, Fan J, Tian Z, Wang C. PPLC-Net : neural network-based plant disease identification model supported by weather data augmentation and multi-level attention mechanism. J King Saud Univ Comput Inf Sci. 2023;35(5):101555. https://doi.org/10.1016/j.jksuci.2023.101555.
44. P. B. R and A. V V. 2022. Tomato leaf disease detection and classification using Cnn. 71 4 2921–2930
45. M. S. Anari. A hybrid model for leaf diseases classification based on the modified deep transfer learning and ensemble approach for agricultural aiot-based monitoring," vol. 2022.
46. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques Process. Inf Agric. 2016. https://doi.org/10.1016/j.inpa.2016.10.005.
47. E. Saraswathi and J. FarithaBanu. A novel ensemble classification model for plant disease detection based on leaf images. 2023.
48. Altalak M, Uddin MA, Alajmi A, Rizg A. A hybrid approach for the detection and classification of tomato leaf diseases. Appl Sci. 2022;12:1–14.
49. Nawaz M, et al. OPEN A robust deep learning approach for tomato plant leaf disease localization and classification. Rep Sci. 2022. https://doi.org/10.1038/s41598-022-21498-5.
50. Garg S, Singh P. An aggregated loss function based lightweight few shot model for plant leaf disease classification. Multimedia Tools Appl. 2023;10(23797–23815):2023.
51. Yigezu MG, Woldeyohannis MM, Tonja AL. Early ginger disease detection using deep learning approach. Berlin: Springer International Publishing; 2022.
52. P. Nayar, S. Chhibber, and A. K. Dubey, "An Efficient Algorithm for Plant Disease Detection Using Deep Convolutional Networks," Proceedings - 2022 14th IEEE International Conference on Computational Intelligence and Communication Networks, CICN 2022. pp. 156–160, 2022
53. Kukadiya H, Meva D. Automatic cotton leaf disease classification and detection by convolutional neural network. Berlin: Springer Nature Switzerland; 2022.
54. Mengistu AD, Mengistu SG, Melesew D. An automatic coffee plant diseases identification using hybrid approaches of image processing and decision tree. Indones J Electr Eng Comput Sci. 2018;9(3):806–11. https://doi.org/10.11591/ijeecs.v9.i3.pp806-811.

55. Darma Putra IKG, Jayantha Putra IPD, Fauzi R. Witarsyah classification of tomato plants diseases using convolutional neural network. Int J Adv Sci Eng Inf Technol. 2020;10(5):1821–7.
56. Gangwar A, Rani G, Dhaka VPS. detecting tomato crop diseases with Ai: leaf segmentation and analysis. Int Conf Trends Electron Inform. 2023. https://doi.org/10.1109/ICOEI56765.2023.10125891.
57. E. B. Paulos and M. M. Woldeyohannis. Detection and classification of coffee leaf disease using deep learning," no. January 2023, 2022. https://doi.org/10.1109/ICT4DA56482.2022.9971300.
58. Shoaib M, et al. Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease. Front Plant Sci. 2022;13:1–18. https://doi.org/10.3389/fpls.2022.1031748.
59. Attallah O. Tomato leaf disease classification via compact convolutional neural networks with transfer learning and feature selection. Horticulturae. 2023. https://doi.org/10.3390/horticulturae9020149.
60. Ksibi A, Ayadi M, Soufiene BO, Jamjoom MM, Ullah Z. MobiRes-net: a hybrid deep learning model for detecting and classifying olive leaf diseases. Appl Sci. 2022. https://doi.org/10.3390/app122010278.
61. Shovon MSH, Mozumder SJ, Pal OK, Mridha MF, Asai N, Shin J. PlantDet: a robust multi-model ensemble method based on deep learning for plant disease detection. IEEE Access. 2023;11(April):34846–59. https://doi.org/10.1109/ACCESS.2023.3264835.
62. Albattah W, Nawaz M, Javed A, Masood M, Albahli S. A novel deep learning method for detection and classification of plant diseases. Complex Intell Syst. 2022;8(1):507–24. https://doi.org/10.1007/s40747-021-00536-1.
63. Trivedi NK, et al. Early detection and classification of tomato leaf disease using high-performance deep neural network. Sensors. 2021. https://doi.org/10.3390/s21237987.
64. Al-gaashani MSAM, Shang F, Muthanna MSA, Khayyat M, El-Latif AAA. Tomato leaf disease classification by exploiting transfer learning and feature concatenation". IET Image Process. 2022. https://doi.org/10.1049/ipr2.12397.
65. Thanh LVN, Ahderom S, Apopei B, Alameh K. A novel method for detecting morphologically similar crops and weeds based on the combination of contour masks and filtered Local Binary Pattern operators. Gigascience. 2020;9(3):1–16. https://doi.org/10.1093/gigascience/giaa017.
66. Ahmad W, Shah SMA, Irtaza A. Plants disease phenotyping using quinary patterns as texture descriptor. KSII Trans Internet Inf Syst. 2020;14(8):3312–27. https://doi.org/10.3837/tiis.2020.08.009.
67. G. Kuricheti and P. Supriya. Computer vision based turmeric leaf disease detection and classification: a step to smart agriculture. 2019. https://doi.org/10.1109/ICOEI.2019.8862706.
68. A. Abbas, S. Jain, M. Gour, and S. Vankudothu. Tomato plant disease detection using transfer learning with C-GAN synthetic images. 2021.
69. Panigrahi KP, Das H, Sahoo AK. Maize leaf disease detection and classification using machine learning maize leaf disease detection and classification using machine intell. Adv Syst Comput. 2020. https://doi.org/10.1007/978-981-15-2414-1.
70. Kanuparthi P, Bejgam V, Viswanatham VM. A novel approach of ensembling the transfer learning methods for rice plant disease detection and classification. WEB. 2021. https://doi.org/10.14704/WEB/V18I2/WEB18331.
71. Prabhakar M, Purushothaman R, Awasthi DP. Deep learning based assessment of disease severity for early blight in tomato crop. Multimed Tools Appl. 2020;79(39–40):28773–84. https://doi.org/10.1007/s11042-020-09461-w.
72. Ahmed S, Hasan MB, Ahmed T, Sony MRK, Kabir MH. Less is more: lighter and faster deep neural architecture for tomato leaf disease classification. IEEE Access. 2022;10(June):68868–84. https://doi.org/10.1109/ACCESS.2022.3187203.
73. Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E. "Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics. 2021. https://doi.org/10.3390/electronics10121388.
74. Zhao S, Peng Y, Liu J, Wu S. Tomato leaf disease diagnosis based on improved convolution neural network by attention module. Agric. 2021. https://doi.org/10.3390/agriculture11070651.
75. Ashok S, Kishore G, Rajesh V, Suchitra S, Gino Sophia SG, Pavithra B. Tomato leaf disease detection using deep learning techniques. Proc 5th Int Conf Commun Electron Syst. 2020. https://doi.org/10.1109/ICCES48766.2020.09137986.
76. Sreelatha P, Udayakumar MS, Karthick S, Ch SC, Kavya KCS, Madiajagan M. Managing the tomato leaf disease detection accuracy using computer vision based deep neural network. J Contemp Issues Bus Gov. 2021;27(1):3425–37.
77. Maeda-Gutiérrez V, et al. Comparison of convolutional neural network architectures for classification of tomato plant diseases. Appl Sci. 2020. https://doi.org/10.3390/app10041245.
78. Batool A, Hyder SB, Rahim A, Waheed N, Asghar MA. Classification and identification of tomato leaf disease using deep neural network. 2020 Int Conf Eng Emerg Technol ICEET. 2020. https://doi.org/10.1109/ICEET48479.2020.9048207.
79. Zaki SZM, Zulkifley MA, Mohd Stofa M, Kamari NAM, Mohamed NA. Classification of tomato leaf diseases using mobilenet v2. IAES Int J Artif Intell. 2020. https://doi.org/10.11591/ijai.v9.i2.pp290-296.
80. Bhatia A, Chug A, Singh AP. Hybrid SVM-LR classifier for powdery mildew disease prediction in tomato plant. Int Conf Signal Process Integr Networks. 2020. https://doi.org/10.1109/SPIN48934.2020.9071202.
81. Geetharamani G. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput Electr Eng. 2019;76:323–38. https://doi.org/10.1016/j.compeleceng.2019.04.011.
82. Aziz S, Bashir M, Mughal O, Khan MU, Khan A. Image pattem classification for plant disease identification using local tri-directional featuresInf. Electron Mob Commun Conf IEMCON Technol. 2029. https://doi.org/10.1109/IEMCON.2019.8936236.
83. Thangaraj R, Anandamurugan S, Kaliappan VK. Automated tomato leaf disease classification using transfer learning-based deep convolution neural network. J Plant Dis Prot. 2021;128(1):73–86. https://doi.org/10.1007/s41348-020-00403-0.
84. Agarwal M, Singh A, Arjaria S, Sinha A, Gupta S. ToLeD: tomato leaf disease detection using convolution neural network. Procedia Comput Sci. 2020;167(2019):293–301. https://doi.org/10.1016/j.procs.2020.03.225.
85. Agarwal M, Gupta SK, Biswas KK. Development of efficient CNN model for tomato crop disease identification. Sustain Comput Informatics Syst. 2020;28: 100407. https://doi.org/10.1016/j.suscom.2020.100407.

86. Sandhu GK, Kaur R. "Plant disease detection techniques: a review", 2019. Int Conf Autom Comput Technol Manag ICACTM. 2019;2019:34–8. https://doi.org/10.1109/ICACTM.2019.8776827.
87. Meena Prakash R, Saraswathy GP, Ramalakshmi G, Mangaleswari KH, Kaviya T. Detection of leaf diseases and classification using digital image processing. Int Conf Innov Information Embed Commun Syst ICIIECS Proc. 2018. https://doi.org/10.1109/ICIIECS.2017.8275915.
88. M. Rashid, B. Ram, R. S. Batth, N. Ahmad, and H. M. E. I. Dafallaa. Novel image processing technique for feature detection of wheat crops using python openCV.
89. Krithika P, Veni S. "Leaf disease detection on cucumber leaves using multiclass support vector machine. Proc Int Conf Wirel Commun Signal Process Networking WiSPNET. 2017. https://doi.org/10.1109/WiSPNET.2017.8299969.
90. Burhan SA, Minhas DS, Tariq DA, Nabeel Hassan M. Comparative study of deep learning algorithms for disease and pest detection in rice crops. Proc Conf Electron Comput Artif Intell ECAI Int. 2020. https://doi.org/10.1109/ECAI50035.2020.9223239.
91. Hasan MJ, Mahbub S, Alom MS, Abu Nasim M. Rice disease Identification and classification by integrating support vector machine with deep convolutional neural network. 1st Int Conf Adv Sci Eng Robot Technol. 2019. https://doi.org/10.1109/ICASERT.2019.8934568.
92. Vaishnnave MP, Suganya Devi K, Srinivasan P, Arutperumjothi G. Detection and classification of groundnut leaf diseases using KNN classifier. Int Conf Syst Comput Autom Networking ICSCAN. 2019. https://doi.org/10.1109/ICSCAN.2019.8878733.
93. Padol PB, Yadav AA. SVM classifier based grape leaf disease detection. Conf Adv Signal Process CASP. 2016;2016:175–9. https://doi.org/10.1109/CASP.2016.7746160.
94. Dandawate Y, Kokare R. An automated approach for classification of plant diseases towards development of futuristic decision support system in Indian perspective. Int Conf Adv Comput Commun Inform ICACCI. 2015. https://doi.org/10.1109/ICACCI.2015.7275707.
95. Hari SS, Sivakumar MM, Renuga DP, Karthikeyan S, Suriya S. Plant disease detection by leaf image classification using convolutional neural network. Comput Sci Commun Inf. 2019. https://doi.org/10.1007/978-981-15-1384-8_16.
96. Jenifa A, Ramalakshmi R, Ramachandran V. Cotton leaf disease classification using deep convolution neural network for sustainable cotton production. 2019 Int Conf Clean Energy Energy Effic Electron Circuit Sustain Dev INCCES 2019. 2019. https://doi.org/10.1109/INCCES47820.2019.9167715.
97. Anand R, Veni S, Aravinth J. An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method. Int Conf Recent Trends Inf Technol ICRTIT. 2016. https://doi.org/10.1109/ICRTIT.2016.7569531.
98. Durmus H, Gunes EO, Kirci M. Disease detection on the leaves of the tomato plants by using deep learning agrogeoinformatics. Conf Agro-Geoinformatics. 2027. https://doi.org/10.1109/Agro-Geoinformatics.2017.8047016.
99. Nithish EK, Kaushik M, Prakash P, Ajay R, Veni S. Tomato leaf disease detection using convolutional neural network with data augmentation. Proc Int Conf Commun Electron Syst ICCES. 2020. https://doi.org/10.1109/ICCES48766.2020.09138030.
100. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques. Inf Process Agric. 2017;4(1):41–9. https://doi.org/10.1016/j.inpa.2016.10.005.
101. Sun G, Jia X, Geng T. MPlant diseases recognition based on image processing technology. J Electr Comput Eng. 2018. https://doi.org/10.1109/6.100908.
102. Chandramouleeswaran S, Senthil Kumar MD, Professor A. Plant infection detection using image processing. Int J Mod Eng Res. 2018;8:13–6.
103. Ahmad Supian MB, Madzin H, Albahari E. Plant disease detection and classification using image processing techniques: a review. Proc 2019 2nd Int Conf Appl Eng ICAE 2019. 2019. https://doi.org/10.1109/ICAE47758.2019.9221712.
104. Halder M, Sarkar A, Bahar H. Plant disease detection by image processing: a literature review. SDRP J Food Sci Technol. 2018;3(6):534–8. https://doi.org/10.25177/jfst.3.6.6.
105. Ghosal S, Sarkar K. Rice leaf diseases classification using CNN with transfer learning. IEEE Calcutta Conf CALCON. 2020. https://doi.org/10.1109/CALCON49167.2020.9106423.
106. Devaraj A, Rathan K, Jaahnavi S, Indira K. Identification of plant disease using image processing technique. Proc 2019 IEEE Int Conf Commun Signal Process ICCSP 2019. 2019. https://doi.org/10.1109/ICCSP.2019.8698056.
107. Suresh M, Gopinath D, Hemavarthini M, Jayanthan K, Krishnan M. Plant disease detection using image processing. Int J Eng Res Technol. 2022. https://doi.org/10.1007/978-981-15-4032-5_83.
108. Iqbal MA, Talukder KH. Detection of potato disease using image segmentation and machine learning 2020. Int Conf Wirel Commun Signal Process Networking. 2020. https://doi.org/10.1109/WiSPNET48689.2020.9198563.
109. Ali-Al-Alvy M, Khan GK, Alam MJ, Islam S, Rahman M, Rahman MS. Rose plant disease detection using deep learning. Conf Trends Electron Inform. 2023;3(03):1244–9. https://doi.org/10.1109/ICOEI56765.2023.10126031.
110. Howlader MR, Habiba U, Faisal RH, Rahman MM. "automatic recognition of guava leaf diseases using deep convolution neural network", 2nd Int. Conf Electr Comput Commun Eng ECCE. 2019;2019:1–5. https://doi.org/10.1109/ECACE.2019.8679421.
111. Bhagat Patil AR, et al. A literature review on detection of plant diseases. Eur J Mol Clin Med. 2020;7(07):1606.
112. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016;7:1–10. https://doi.org/10.3389/fpls.2016.01419.
113. Ranjan M, Rajiv Weginwar M, Joshi N, Ingole A. Detection and classification of leaf disease using artificial neural network. Int J Tech Res Appl. 2015;3(3):331–3.
114. Ramya V, Lydia MA. leaf disease detection and classification using neural networks. Int J Adv Res Comput Commun Eng. 2016;5(11):207–10. https://doi.org/10.17148/IJARCCE.2016.51144.
115. Patil R, Gulvani S. plant disease detection using neural network : a review. J Emerg Technol Innov Res. 2019;6(2):151–5.

116. Amjad K, Ghous H. Critical review on multi-crops leaves disease detection using artificial intelligence methods. Int J Sci Eng Res. 2021;12:2.
117. Singh MK, Chetia S. Detection and classification of plant leaf diseases in image processing using MATLAB. Int J Life Sci Res. 2017;5(4):120–4.
118. Raut S, Ingole K. Review on fruit disease detection using image processing techniques. Int Res J Eng Technol. 2017;4(4):22–4.
119. Ramakrishnan M, Sahaya ANA. "Groundnut leaf disease detection and classification by using back probagation algorithm", 2015 Int. Conf Commun Signal Process ICCSP. 2015;2015:964–8. https://doi.org/10.1109/ICCSP.2015.7322641.
120. Ngugi LC, Abelwahab M, Abo-Zahhad M. Recent advances in image processing techniques for automated leaf pest and disease recognition—a review. Inf Process Agric. 2021;8(1):27–51. https://doi.org/10.1016/j.inpa.2020.04.004.
121. Ishak S, Rahiman MHF, Kanafiah SNAM, Saad H. Leaf disease classification using artificial neural network. J Teknol. 2015;77(17):109–14. https://doi.org/10.11113/jt.v77.6463.
122. Hrishikesh KP, Lokhande SS. detection and classification of plant leaf diseases using ANN. Int J Sci Eng Res. 2013;4(8):1777–80.
123. Sachdeva G, Singh P, Kaur P. Plant leaf disease classification using deep convolutional neural network with bayesian learning. Mater Today Proc. 2021;45:5584–90. https://doi.org/10.1016/j.matpr.2021.02.312.
124. Kaur P, Harnal S, Tiwari R, Upadhyay S, Bhatia S, Mashat A. Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction. Sensors. 2022. https://doi.org/10.3390/s22020575.
125. Kiani E, Mamedov T. Identification of plant disease infection using soft-computing: application to modern botany. Procedia Comput Sci. 2017;120:893–900. https://doi.org/10.1016/j.procs.2017.11.323.
126. Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui, and C. Jia, "Apple leaf disease identification using genetic algorithm and correlation based feature selection method." 2017.
127. Patil NS. Identification of paddy leaf diseases using evolutionary and machine learning methods. Turkish J Comput Math Educ. 2021;12(2):1672–86. https://doi.org/10.17762/turcomat.v12i2.1503.
128. S. Jasrotiaa, J. Yadava, N. Rajpala, M. Arorab, and J. Chaudhary, "Convolutional Neural Network Based Maize Plant Disease Identification." pp. 1712–1721, 2023.
129. Rekha ASRMG. Detection of unhealthy plant leaves using image processing with arduin. CIKITUSI J Multidiscip Res. 2019;6(3):163–7. https://doi.org/10.35940/ijitee.b1233.1292s419.
130. Nagamani HS, Saroja DH. Research methods for plant health detection using computer vision techniques: a survey. Int J Appl Eng Res. 2019;14(7):1627. https://doi.org/10.3622/ijaer/14.7.2019.1627-1632.
131. Hassan RJ, Abdulazeez AM. Plant leaf disease detection by using different classification techniques comparative. Asian J Res Comput Sci. 2021. https://doi.org/10.9734/ajrcos/2021/v8i430205.
132. Mohanapriya K, Balasubramani M. Recognition of unhealthy plant leaves using naive bayes classifier. IOP Conf Ser Mater Sci Eng. 2016. https://doi.org/10.1088/1757-899X/561/1/012094.
133. FRF Padao EA Maravillas. 2026. Using Naïve Bayesian method for plant leaf classification based on shape and texture features Humanoid, Nanotechnology. Inf Technol Commun Control Environ Manag Conf. https://doi.org/10.1109/HNICEM.2015.7393179
134. Sharma R, et al. Plant disease diagnosis and image classification using deep learning. Comput Mater Contin. 2022;71(2):2125–40. https://doi.org/10.32604/cmc.2022.020017.
135. Prof.D.D.Pukale, G. Kokru, S. Nadar, S. Dhar, and S. Singh. 2019. A disease prediction and rectification system for banana plant. 6, no. 5, pp. 535–539,.
136. FarhanAlHaque ASM, Hafiz R, Hakim MA, RasiqulIslam GM. Computer vision system for guava disease detection and recommend curative solution using deep learning approach. Int Conf Comput Inf Technol ICCIT. 2019. https://doi.org/10.1109/ICCIT48885.2019.9038598.
137. Singh A, Kaur H. Potato plant leaves disease detection and classification using machine learning methodologies. IOP Conf Ser Mater Sci Eng. 2021;1022:1–10. https://doi.org/10.1088/1757-899X/1022/1/012121.
138. Elfatimi E, Eryigit R, Elfatimi L. Beans leaf diseases classification using mobilenet models. IEEE Access. 2022;10:9471–82. https://doi.org/10.1109/ACCESS.2022.3142817.
139. Zhang X, Qiao Y, Meng F, Fan C, Zhang M. Identification of maize leaf diseases using improved deep convolutional neural networks. IEEE Access. 2018;6:30370–7. https://doi.org/10.1109/ACCESS.2018.2844405.
140. Zaki MA, Narejo S, Ahsan M, Zai S, Anjum MR, Din NU. Image-based onion disease (purple blotch) detection using deep convolutional neural network. Int J Adv Comput Sci Appl. 2021;12(5):448–58. https://doi.org/10.14569/IJACSA.2021.0120556.
141. Bal F, Kayaalp F. Review of machine learning and deep learning models in agriculture. Int Adv Res Eng J. 2021;5(2):309–23. https://doi.org/10.35860/iarej.848458.
142. Wang Y, Wang H, Peng Z. Rice diseases detection and classification using attention based neural network and bayesian optimization. Expert Syst Appl. 2021;178:1–11. https://doi.org/10.1016/j.eswa.2021.114770.
143. M. Govardhan and V. M. B, "Diagnosis of tomato plant diseases using random forest." 2019.
144. Devi N, et al. Categorizing diseases from leaf images using a hybrid learning model. Symmetry. 2021;13(11):1–14. https://doi.org/10.3390/sym13112073.
145. Thilagavathi K, Kavitha K, Praba RD, Arina SVAJ, Sahana RC. Detection of diseases in sugarcane using image processing techniques. Biosci Biotechnol Res Commun. 2020;13(11):109–15. https://doi.org/10.21786/bbrc/13.11/24.
146. Aduwo JR, Mwebaze E, Quinn JA. "Automated vision-based diagnosis of cassava mosaic disease. Proc ICDM Work Data Min Agric. 2010;1:1–9.
147. Lamba M, Gigras Y, Dhull A. Classification of plant diseases using machine and deep learning. Open Comput Sci. 2021;11(1):491–508. https://doi.org/10.1515/comp-2020-0122.
148. Khan F, Zafar N, Tahir MN, Aqib M, Waheed H, Haroon Z. A mobile-based system for maize plant leaf disease detection and classification using deep learning. Front Plant Sci. 2023;14(May):1–18. https://doi.org/10.3389/fpls.2023.1079366.

149. Rekha V, Reddy LV, Chaudhari SV, Gopi A, Nithiya C, Ahamed SK. Automated deep learning with wavelet neural network based rice plant classification internet things. Proc Technol. 2023. https://doi.org/10.1109/IDCIoT56793.2023.10053487.
150. Hasan RI, Yusuf SM, Mohd Rahim MS, Alzubaidi L. Automatic clustering and classification of coffee leaf diseases based on an extended kernel density estimation approach. Plants. 2023. https://doi.org/10.3390/plants12081603.
151. Kirti N. A multi-crop disease identification approach based on residual attention learning. J Intell Syst. 2023. https://doi.org/10.1515/jisys-2022-0248.
152. Ullah N, Khan JA, Almakdi S, El-rashidy N, El-sappagh S, Ali F. An effective approach for plant leaf diseases classi fi cation based on a novel deepplantnet deep learning model. Plant Sci Front. 2023. https://doi.org/10.3389/fpls.2023.1212747.
153. Alghamdi H, Turki T. PDD-Net: plant disease diagnoses using multilevel and multiscale convolutional neural network features. Agric. 2023. https://doi.org/10.3390/agriculture13051072.
154. Ulutaş H, Aslantaş V. Design of efficient methods for the detection of tomato leaf disease utilizing proposed ensemble CNN model. Electron. 2023. https://doi.org/10.3390/electronics12040827.
155. Bajpai C, Sahu R, Naik KJ. Deep learning model for plant-leaf disease detection in precision agriculture. IJISTA. 2023. https://doi.org/10.1504/IJISTA.2023.130562.
156. Ahmed M, Ahmed A. Palm tree disease detection and classification using residual network and transfer learning of inception ResNet. PLoS ONE. 2023. https://doi.org/10.1371/journal.pone.0282250.
157. Chauhan D, Walia R, Singh C, Deivakani M, Kumbhkar M. Detection of maize disease using random forest classification algorithm. Turkish J Comput Math Educ. 2021;12(9):715–20.
158. Jadon S. SSM-Net for plants disease identification in low data regime. IEEE ITU Int Conf Artif Intell Good. 2020. https://doi.org/10.1109/AI4G50087.2020.9311073.
159. Mugithe PK, Mudunuri RV, Rajasekar B, Karthikeyan S. Image processing technique for automatic detection of plant diseases and alerting system in agricultural farms ICCSP IEEE. Int Conf Commun Signal Process. 2020. https://doi.org/10.1109/ICCSP48568.2020.9182065.
160. Ganguly SSN. A survey on image processing techniques for glaucoma detection. Int J Eng Res Technol. 2016;4(29):1–5.
161. Simhadri CG, Kondaveeti HK. Automatic recognition of rice leaf diseases using transfer learning. Agronomy. 2023;13(4):1–25. https://doi.org/10.3390/agronomy13040961.
162. Jackulin C, Murugavalli S. "A comprehensive review on detection of plant disease using machine learning and deep learning approaches. Meas Sensors. 2022;24:100441. https://doi.org/10.1016/j.measen.2022.100441.
163. Jung M, et al. Construction of deep learning-based disease detection model in plants. Sci Rep. 2023;13(1):1–13. https://doi.org/10.1038/s41598-023-34549-2.
164. Hari P, Singh MP. A lightweight convolutional neural network for disease detection of fruit leaves. Neural Comput Appl. 2023;35(20):14855–66. https://doi.org/10.1007/s00521-023-08496-y.
165. Mohammed L, Yusoff Y. Detection and classification of plant leaf diseases using digtal image processing methods: a review. ASEAN Eng J. 2023;13(1):1–9. https://doi.org/10.11113/aej.V13.17460.
166. Tholkapiyan M, Devi BA, Bhatt D, Kumar ES, Kirubakaran S, Kumar R. Performance analysis of rice plant diseases identification and classification methodology. Wireless Pers Commun. 2023. https://doi.org/10.1007/s11277-023-10333-3.
167. Li L, Zhang S, Wang B. "Plant disease detection and classification by deep learning—a review. IEEE Access. 2021;9:56683–98. https://doi.org/10.1109/ACCESS.2021.3069646.
168. Nguyen C, Sagan V, Maimaitiyiming M, Maimaitijiang M, Bhadra S, Kwasniewski MT. Early detection of plant viral disease using hyperspectral imaging and deep learning. Sensors. 2021;21(3):1–23. https://doi.org/10.3390/s21030742.

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