Scope
Volume 14 Number 02 June 2024

A Research Review and Perspective towards Plant Leaf Disease Detection using Image Processing Techniques

Amrita Arjun Kindalkar

Research Scholar, Department of CS&E, Srinivas University Institute of Engineering and Technology, Srinivas University, Mukka, Managalore, 574 146.
Email: ammukindalkar@gmail.com

Dr. J.Venkata Krishna

Associate Professor, Department of CSE , Srinivas University Institute of Engineering and Technology, Srinivas University, Mukka, Managalore, 574 146. Email:venkatakrishna.janapati@gmail.com

Abstract-Plant Leaf Disease (PLD) detection is helpful for several fields like Agriculture Institute and Biological Research. The country's economic growth depends on the productivity of the agricultural field. Recently developed models based on deep learning give more accurate and precise results over the detection and classification of PLD while evolving through image processing approaches. Many image processing are used for the identification and classification of PLD. The quality of agricultural products is mainly affected by several factors like fungi, bacteria, and viruses. Thesefactors severely destroy the entire growth of the plant. Hence, some outperformed models are needed to detect and identify the severity level of plant diseases yet, the identification requires more time and has astruggle to identify theappropriate type of disease based on its symptoms. Therefore, several automatic detection and classification models are developedto avoid the time complexity. Computerized image processing approaches are utilized for crop protection, which analyzes the color information of leaves from the collected images. Hence, image processing techniques play an important role in the identification and classification of PLD. It gives more advantages by lowering the task of illustrating crops on large farms and detecting the leaf diseases at theinitial stage itself based on the symptoms of the plant leaves. While implementing a new model, there is a need to study various machine and deep learning-based structures for PLD detection approaches. This research work provides an overview of variousheuristic approaches, machine learning, and deep learning models for the detection and classification of PLD. This research work also covers the various constraints like PLD detection tools, performance measures, datasets used, and chronological review. Finally, the research work explores the research findings and also the research gaps with future scope.

Keywords-Plant Leaf Diseases; Leaf Images; Image Processing Approaches; Deep Learning Algorithms; Machine Learning Algorithms; Performance Measures; Research Gaps; Utilization of Tools; Used Datasets;

1. Plant leaf disease detection: General image processing steps, literature review, and chronological review

1.1 Image Processing Steps

Agriculture is a significant factor in providing food and day by day it helps to improve economic growth. Economic growth broadly depends on the growth of agricultural plants and the profit obtained from agricultural farms (Zhao Y. et al. 2022) [1]. Plants are greatly affected by plant diseases which destroy the plant growth and reduce the economic growth of the farmer (Albattah W. et al. 2022) [2]. Plants are infected by distinct types of diseases that affect the parts of the plants, fruit, seed, stem, leaves, and so on (Sunil C. K. et al. 2022) [3]. Leaves are the core part of the plant because the photosynthesis process takes place only in the leaves of the plant, and plant growth mainly relies on the photosynthesis process (Mahato D. K. et al. 2022) [4]. The leaves of plants are easily infected by viral diseases like bacterial, and fungal diseases, and also several environmental factors (Zeng Q. et al. 2020) [5]. Hence, there is a need to detect and classify the diseases automatically with less execution time (Moussafir M. et al. 2022) [6].

The automatic PLD detection techniques give the way to solve the problems and aid inimproving the robustness and accuracy of the outcome (Amin H. et al. 2022) [7]. Here, the accuracy of classification is enhanced by performing image processing. Generally, image processing techniques are utilized in PLD for detecting the infections or diseases present in the leaves by considering the changed color of the leaf. Furthermore, these techniques functioned well over sample images collected from all lighting conditions. Most of the PLD models employ image processing strategies to the collected images and carry out the further process (Saleem M. H. et al. 2022) [8]. The processeslike feature extraction, segmentation, image acquisition, preprocessing, and classification will be employed after executing the image processing (Jiang P. et al. 2019a) [9].

The collected leaf images are present in various dimensions, and further, the obtained images undergo preprocessing to give thesame dimension (Barburiceanu, S. et al. 2021) [10], reducing background, noises, and other unwanted distortions to get high-quality images (Chen J. et al. 2022) [11]. Then these preprocessed images are given to the segmentation processto get the region of interest that represents the affected region (Dwivedi R. et al. 2022) [12]. Using this image segmentation technique, the infected portion is easily identified, and helps to enhance the accuracy of the PLD process (Reddy S. R. G. et al. 2022) [13]. After segmentation, the relevant features are extracted from the obtained region of interest with theinfected part (Kaur P. et al. 2022) [14]. Finally, the retrieved features are fed to the machine learning or deep learning-based classification models (Gunisetti L. et al. 2022) [15] to increase the efficiency of the PLD classification (Nawaz M. et al. 2022a) [16]. The structural illustration of the image processing steps is given in the below Fig 1.

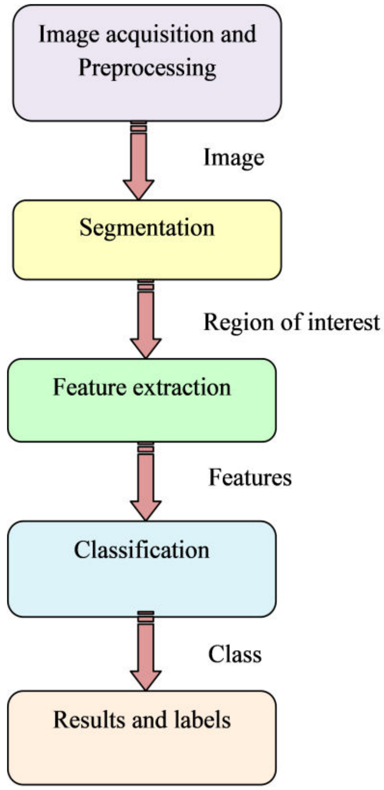


Figure 1. Steps involved in the PLD detection model using image processing

Different steps are utilized for preprocessing the images, segmentation, (Suresh & Seetharaman, K. 2022) [17] feature retrieval, and classification for improving the robustness of the PLD detection and classification systems (Pradhan, P. et al. 2022) [18]. The crucial intention of this image processing technique is to reducethe computational complexity, execution time, and implementation cost.

Image preprocessing approaches aid in enhancing the quality of images by diminishing the distortions, blurs, and noises in the collected images, and alsohelp to enhance the relevant features for further disease classification process. In PLD, image processing techniques areadopted to enhance the quality of the images, color space conversion, image transformation, image translation, filtering, and so on. In most of the PLD models, the color space conversion technique is used because the Hue Saturation Value(HSV) is the superlative tool for color perception. Hence, the RGB color is changed into HSV. Moreover, the histogram equalization methods are mostly adopted in image preprocessing and it is a graphical representation of the intensity transmission of an image. This transmission of intensities may enhance the image contrast from local to higher levelto improve the quality, visibility, and interpretability of images.

The deep learning and machine learning-based approaches solve several complexities presentin the PLD detection models (Gajjar, R. et al. 2022) [19]. The deep learning-based detection mechanism detects the diseases and it alsoeffectively estimates the severity level of the diseases. Moreover, the simple detection approaches include partial classification and real-time monitoring. For detecting the diseases, neural networks are adopted to reveal if the sample leaves are infected by the diseases. Dual-segmented regression analysis is used for early detection of calcium deficiencies in the images. The nutrient deficiencies are efficiently identified under all lighting conditions using this regression-based technique.

This survey will help the researchers explore future perspectives to provide brief summarization of the PLD detection and classification models (Mustafa, H. et al. 2022) [20].

The important contributions of this survey are described below.

- To formulate a brief survey based on traditional PLD identification and classification models with various strategies by gathering data through feature extraction and segmentation processes using machine and deep network-based approaches.
- To provide a progressive study about the use of preprocessing, feature extraction, segmentation, and classification techniques for PLD identification using traditional models.
- To give an elaborative summarization of the collected plants, datasets, implementation tools, type of leaf disease to be detected, and the performance measures assist in implementing the PLD identification model.
- To enumerate the significant research gaps and the drawbacks in the traditional PLD identification approaches to encourage the researchers to develop effective leaf disease identification approaches with several improvements.

The workflow of this survey is briefly explained as follows: conventional machine and deep structure-based PLD identification models are explained in section I. Implementation tools and the type of preprocessing steps, segmentation algorithms, feature extraction models, and the classification networks used for the PLD identification are given in section II. The type of plant, various types of diseases, performance measures, and the datasets utilized are discussed in Section III. Research Gaps and the challenges of the conventional PLD detection approaches are summarized in Section IV.

1.2 Literature Review

Prasad, S. et al. (2012) [21] have recommended an efficient PLD approach using Gabor wavelet transform and SVM classifier. Initially, histogram-based segmentation,feature retrieval, and matching were done to detect the diseases to improve the production rate. Gurjar A. A and Gulhane V. A. (2012) [22] have developed a leaf disease detection approach for cotton leaves with the usage of eigenfeature regularization with an extraction model. The discriminant featureevaluation was performed to formulate the Eigen spectrum and the dimensionality of the featureswas reduced. Jing-Cheng Z. et al. (2012) [23] have developed a continuous wavelet analysis to estimate the extent of the disease more accurately than previous methods for detecting diseases of the leaves of wheat plants by employing the powdery mildew across a spectroscopy level. Samanta D and Ghosh, A. (2012) [24] have designed a histogram-based model for Maize leaf disease classification using preprocessing, segmentation, and feature extraction techniques to appropriately identify the type of diseases. Finally, they suggested the disease phase and the consultative module treatmentfor effective performance. In 2012, Kuana *et al.* (Kuana C.-P. et al. 2012) [25] implemented a PCR-based quantization of squash leaf curl virus in the cucurbits. This approach wasathousand times more effective than the traditional PCR-based PLD detection approaches.

Aji A. F. et al. (2013) [26] have suggested a PLD detection model for palm leaves using neural network-based image processing approaches. Totally, 6 types of features were retrieved and the leaf diseases were effectively classified with higher accuracy. Revathi P. and Hemalatha M. (2013) [27] haveproposed a crop leaf disease classification approach based on a machine learning technique like,a deep forward neural network and cross-information gain-based minimal resource allocation schemesto detect the PLD. Arivazhagan S. et al. (2012) [28] have developed a novel SVM-based model that used extracted textural features to classify PLD and identify diseased areas in plant leaves. Additionally, the green pixels were masked and fully eliminated from the original image utilizinga specific threshold value-based segmentation process. Zhou R. et al. (2013) [29] have suggested adaptive-oriented code pairing, a reliable illness diagnosis technique derived from a reliable image registration system. The main goal was detecting the continuous and site-specific changes in plant diseases with the utilization of the developed algorithm. Al-Tarawneh, M. S. (2013) [30] has suggested an olive leaf spot disease detection approach by using the auto cropping and fuzzy c-means algorithm. The severity rating of the olive leaf spot disease has been effectively analyzed using the developed model. Fadzil W.M.N.W.M. et al. (2014) [31] have recommended an orchid PLD detection modelbased onborder segmentation. Here, the filtering and morphological processing methods wereutilized to improve the image quality. The developed techniqueoffered the potential to identify the leaf diseases at theinitial stage. Hitimana E and Gwun O. (2014) [32] have proposed a coffee leaf infection detection frameworkusing image processing strategies. By eliminating the loss of foliage in the initially taken images, the developed model was able to instinctively assess its intensity factor. The effectiveness of the model wasimproved using the segmentation approach.

Oberti R. et al. (2014) [33] have proposed a grapevine leaf disease detection approach by analyzing the optimal view to enhance the sensitivity. The training phase was performed separately to assess the degree of severity's capacity. Zhang Z. et al. (2014) [34] have implemented an optimization algorithm-assisted deep structures for recognizing maize PLD. The problem-solving capacitycould be improved by the optimizing weight and the threshold value in the neural network classifier. Ranjan M. et al. (2015) [35] have introduced a PLD detection and classification approach using Artificial Neural Networks(ANN) to provide intuitive judgment over plant leaf diseases. The color features were extracted to differentiate the diseased and healthy sample images appropriately. In 2015, Bhange and Hingoliwala (Bhange M. A and Hingoliwala H. A. 2015) [36] developed a bacterial blight detection approach on pomegranate leaves using the k-partitioning approach based on K-means clustering to increase the productivity and economical quality. In 2015, Warne and Ganorkar (Warne P. P and Ganorkar S. R. 2015) [37] introduced a PLD detection approach on cotton leaves using the k-means clustering approach to provide high accuracy. The cotton diseases were effectivelyanalyzed based on the set of features. In 2015, Mokhtar *et al.* (Mokhtar U. et al. 2015) [38] suggested the tomato leaf virusidentification model using SVM and different kernel functions, and the performance was computed using theN-fold cross-validation technique. In 2015, Chandra *et al.* (Karmokar B. C. et al. 2015) [39] implemented a PLD model on tea leaves using the ensemble neural network-based classificationmodel with the adoption of image resizing and feature extraction processesto increase the production of tea leaves and reducing the effect of diseases present in the tea leaves.

In 2015, Hanifa *et al.* (Hanifa A. et al. 2015) [40] designed an adaptive Neuro fuzzy-based PLD detection model on tea leavesemploying color wavelet feature. Extracting the color features helpedto enhance the recognizability of the leaf diseases. In 2016, Nemishte *et al.* (Nemishte, D. et al. 2016) [41] introduced a grape leaf disease recognition model using an acclustering network. The recommended model's primary goal was to identify diseases and carry out remedial activities with a minimum life span. Theproposed model was formulated based on two phases such assegmentation and classification. In 2016, Mondal and Kumar(Mondal D and Kole D. K. 2016) [42] developed a time-efficient leaf rust disease detection approach by adopting the rough fuzzy c-means algorithms. and the person correlation coefficientwas considered to classify the diseased part and the non-diseased part of the wheat leaf images. In 2016, Vipinadas and Thamizharasi(Vipinadas M.J and Thamizharasi A. 2016) [43] implemented an adaptive contrast method to convert digital data to grayscale, retrieve features, and classify the banana leaf disease in order to determine if illnesses impacted the accuracy of the generated model. In 2016, Shi and Zhang (Wang, Y. S. X and

Zhang, S. 2016) [44] proposed an IoT-based PLD identification system with the support of K-means clustering.To improve the precision of detection, the affected image area was separated into various areas and structured around the closest group. In 2016, Sladojevic *et al.* (Sladojevic S. et al. 2016) [45] suggested a deep structure-based PLD recognition approach for classifying the plant leaves based on healthy and unhealthy with higher accuracy. It was the best way to effective detection to facilitate quick access and easy system implementation when compared to other models. In 2016, Qin *et al.* (Qin F. et al. 2016) [46] developed an effectivealfalfa leaf disease classificationframework. Here, several clustering algorithms were integrated to form a new algorithmfor extracting the features, and then the resultant features were fed into regression-based classifiers for identifying the diseases. In 2016, Bihari *et al.* (Padhy J. B. et al. 2016) [47] recommended a PLD detection approach using fuzzy and K-means clustering to decrease the processing time. The steps involved in the developed PLD identification system were preprocessing, segmentation, feature extraction, and classification. Xie C. and He Y. (2016) [48] have proposed an early blight disease identification approach using spectrum and image texture feature analysis on eggplant leaves. The features like dissimilarity, entropy, homogeneity, contrast, dissimilarity, correlation, moment, mean and variance were extracted to improve the effectiveness. Chant, C. D. et al. (2017) [49] have introduced automatic northern leaf blight infection detection on maize plantsutilizing adeep learning strategy for accurately classifying small sections of leaf images and locating the injured part. Jeon W.-S and Rhee S.-Y. (2017) [50] have designed a CNN-based plant leaf recognition approach to classify the leaves by considering the leaf's characteristics. The major contribution of this developed model was to provide better effectiveness over big data. Prashar K. et al. (2017) [51] have proposed a novel leaf disease classification approach via theSVM-based classification modelfor analyzing the texture and form of cotton leaves in order to discover color lighting fluctuations with extreme accuracy. Liu B. et al. (2017) [52] have presented an apple leaf disease recognition method using a deep learning network for enhancing robustness by analyzing the deep features from the images and increasing the convergence rate. Ashqar B. A. M. and Abu-Naser S. S. (2018) [53] have recommended a deep learning-based PLD detection model on tomato leaves, where the tomato leaves were gathered under controlled conditions to find the five types of PLD with high detection accuracy. Veeraballi R. K. et al. (2020) [54] have suggested a novel for the classification of papaya leaf diseases with the support of a deep learning model to enhance the profit under various conditions like complex backgrounds, illumination, and different resolution.

Maa J. et al. (2018) [55] have proposed a DCNN-based cucumber leaf disease classification algorithm based on leaf characteristics of the collected images to derive a successful disease detection accuracy above in-field circumstances. Wanga Z. and Zhang, S. (2018) [56] have designed a corn leaf disease detection model based on the CNN, where the trained image was subjected to upsamplingto get same-size feature maps and then the segmentation process wascarried out to restore the deconvolutioncourse. Ozguven M. M. and Adem K. (2019) [57] have proposed a deep learning strategy for the automatic classification of sugar beet leaf diseases. The parameters present in the CNN were optimized to raise the recognition rate. The execution time could be effectively reduced using the developed approach. Jiang P. et al. (2019b) [58] have employed an improved CNN structure for the identification of apple leaf diseases in real-time. Initially, data augmentation was employed to improve the contrast of the images, and then the image annotation methods were adopted to provide ahigh-performance solution. Singh V. (2019) [59] hasdeveloped an image segmentation strategy for detecting sunflower leaf diseases using a particle swarm optimization mechanism. The affected part was exactly identified using the implemented leaf disease identification approach. Wu Q. et al. (2019) [60] have designed a soybean leaf disease identification method using the transfer learning approach by optimizing the variety of parameters to offer precise detection of soybean leaf diseases. Emebo O. et al. (2019) [61] have designed a deep CNN-based tomato leaf detection approach while enabling the Raspberry Pi device. The affected areas were recognized automatically using the developed model in order to improve accuracy. Azadbakht M. et al. (2019) [62] have implemented a machine learning-basedleaf rust detection approach under various leaf area index levels. The canopy scale was utilized to identify the severity level of the diseases by incorporating some spectral vegetation indices.

Rashid J. et al. (2021) [63] have implemented a deep learning-based multifaceted PLD detection approach on potato leaves. The potato leaves from the potato plants were extracted and then partitioned the image into several regions for detecting the leaf diseasewith high efficiency. Atila Ü. et al. (2019) [64] have developed an EfficientNet structure for the classification of PLD. The developed model did not require any processing stage, but, it could provide efficient classification over detecting PLD. Zhou C. et al. (2020) [65] have employed arestructured deep residual network-based tomato leaf disease recognition method to support farmers in increasing their profit. The suggested network effectively reduced the number of training parameters, and also the complexity based on processing time and computation. Ayu H. R. et al. (2020) [66] have proposed a deep learning strategy-based cassava PLD detection model. The healthy and the unhealthy leaves were effectively identified using the newly implemented PLD identification model. Abed S. H. et al. (2020) [67] have presented a robot vision-based deep learning framework for automatically detecting bean leaf diseases with high accuracy. The input images were collected from uncontrolled environmental conditions and then, the multi-classification task was performed. Shin J. et al. (2020) [68] have suggested a neural network-based model to identify the powdery mildew disease from the strawberry leaves. The developed model successfully reduced the overfitting issues, by considering the different dimensions and shapes of the leaves. Yadav M. G. et al. (2021) [69] have proposed a machine learning-based PLD identification method to provide several benefits such as less time-consuming, non-sensitive, and profitable. This model effectively classified the extent of leaf damage, leaf color, and area of the leaves over unhealthy plants. Chowdhury M. E. H. et al. (2021) [70] have proposed a neural network framework for automatically detecting reliable leaf diseases to reduce the shortcomings of continuous human monitoring systems. Here, two-step segmentation processes were employed to increase the detection accuracy.

Ramkumar G. et al. (2021) [71] have implemented a deep network-based effectual PLD detection method by enabling IoT strategies. The affected regionswereproperly segmented and the disease type waseffectually analyzed using the classification model. Ahmed A.A. and Reddy G.H. (2021) [72] have recommended a deep learning-based PLD recognition approach by adopting mobile devices. The mobile deviceswere utilized to provideauser interface and display the category of the diseases. Singh, A. et al. (2021) [73] have suggested a peach leaf disease identification model for the evaluation of bacteriosis. The developed model providedanearly warning about the diseases when combining unmanned aerial vehicles with uncontrolled laboratory conditions. Poornam S. and Devaraj A. F. S. (2021) [74] have recommended an image-based deep learning approach for detecting the PLD to differentiate the affected and the unaffected leaves. The ten-fold cross-validation function was utilized for validating the performance. Memon M.S. et al. (2022) [75] have presented a meta-deep structure strategy for the identification ofleaf diseases on cotton crops to differentiate the healthy and unhealthy leaves. Moreover, the main goal of this approach was to provide good generalization and accuracy. Malik A. et al. (2022) [76] have implemented a hybrid deep-learning technique to detect sunflower leaf diseases. Here, the merging operation was performed using the stacking ensemble learning approach for leaf disease classification. Jhatial M. J. et al. (2022) [77] have proposed a rice PLD recognition model using aYoloV5 classifier to identify the infected leaves. The proposed scheme mainly focused on agricultural landto enhance the productivity of crops byidentifyingthe PLD at an initial stage. Nawaz M. et al. (2022b) [78] have offered a robust deep network-based tomato leaf disease detection model for localizing and classifying the disease with high accuracy. The presented method's robustness was confirmed by performing the qualitative and quantitative assessments.

Ashwinkumar, S. et al. (2022) [79] have offered an optimal MobileNet model based on CNN for automatically detecting the PLD. The parameters in the developed model were optimized using the Emperor Penguin Optimizer (EPO) to maximize the accuracy. Ma, Z. et al. (2022) [80] have proposed a deep transfer convolution neural networks-based maize leaf disease identification system to determine the disparity between the target and the source imageto improve the usefulness of the developed model. Jiang J. et al. (2022) [81] have proposed a CNN-based PLD classification model on wheat leaf diseases through several evaluation strategies using the collected images to reduce memory requirements and computational time. Noola D. A. and Basavaraju D. R. (2022) [82] have suggested a machine learning approaches-based leaf disease detection model on corn leaf images to offer enhanced outcomes. The developed model provided the best results by analyzing the information like boundary, structural, pattern, and discriminative features. Chen H.-C. et al. (2022) [83] have designed an AlexNet-CNN for the recognition of PLD from tomato leaves, where the total information has been divided into ten labels of tomato leaf diseases with anuncompromising cross-entropy loss function. Ksibi A. et al. (2022) [84] have suggested a hybrid deep structure-based approach for the classification of olive leaf diseases in the grove uncontrolled environment. Here, the deep features were extracted to give high effectiveness over classification. Anitha and Saranya, (2022) [85] have designed a cassava PLD identification model using deep learning structure. The developed technique provided strong guidance for pest control and automatic process control mechanisms over leaf diseases.

1.3 Chronological Review

The chronological review of the conventional PLD identification models based on machine and deep learningconcerningthe published yearsis given in Fig 2. In this survey, we collected various research works from the year 2012 to 2022.

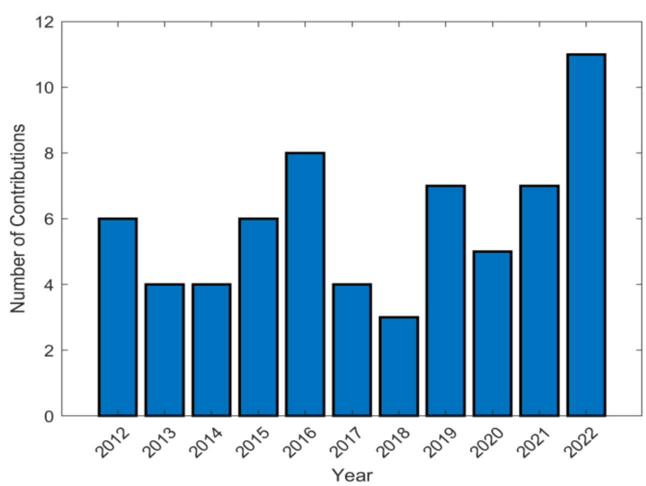


Figure 2.A chronological exploration of the existing deep and machine learning-based PLDdetectionapproaches

1.4 Implemented Tool

The implementation tools for developing the conventional PLD detection approaches are graphically illustrated in Fig 3. Here, 27.69% of research works used MATLAB tool, 12.30% of research works used NVIDIA, 15.38% of research works used Python platform, 7.69% of research works utilized Tensorflow, and 18.46% of research works are considered under miscellaneous type. Most of the existing PLD detection and classification models are constructed using the MATLAB software platform because it minimizes the computational complexity.

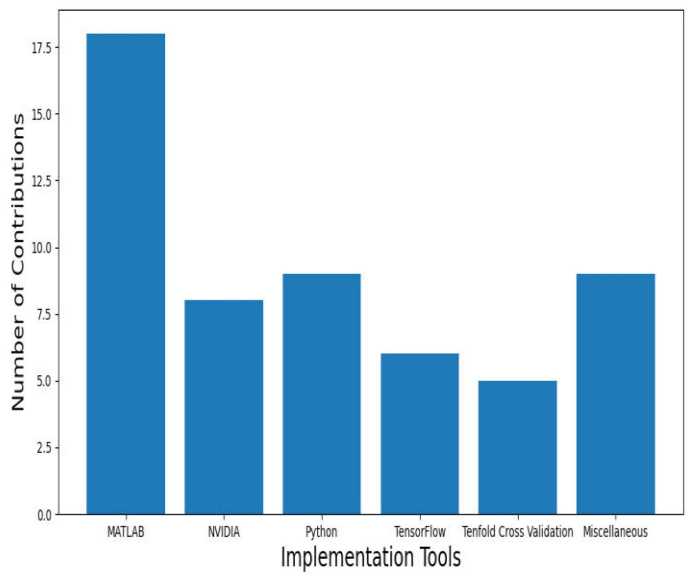


Figure 3. Tools to be used for implementing the PLDdetection approaches

2. Techniques used for diverse PLD detection models

2.1 Pre-processing Techniques

The preprocessing techniques used for detecting the PLD over the existing research works are illustrated in Table I. Thepreprocessing techniques are utilized to enhance the contrast and quality of the image which is necessary for further classification. Here, image enhancement schemes are used to improve image quality, and filtering and artifact removal techniques are used to eliminate the noises and artifacts from the collected images. The garnered leaf images have different sizes and dimensions, and hence, image resizing techniques are needed which supportsreshaping the image with appropriate dimensions.

Image Transformation: Image transformation techniques are mostly adopted in the PLD classification models for changing the dimensions and angles of the image to improve the performance. The image transformation models do not affect the basic formation of the leaf, and the most widely used image transformation approaches are the projective transformation and affine transformation.

Image scaling: Image scaling is used to resize the image as per the requirement. Image enlargingand shrinking operations are performed in image scaling.

Image translation: Changingtheimage into a frame is performed in image translation.

Image filtering: The image filtering process is used to enhance the contrast and external appearance of the images. Moreover, the noise and artifacts in the images are reduced by applying this process.

Color image transformation techniques: Color image transformation techniques are used to improve the color composite of the image by regulating the contrast stretch between the two transformed images.

I. **Table 1.**Preprocessing techniques used for PLD detection

Citation number	Preprocessing Techniques
(Prasad, S. et al. 2012) [21]	Color Thresholding
(Gurjar A. A and Gulhane V. A. 2012) [22]	Filtering, Cropping, Contrast Enhancement and Angle Correction
(Kuana C.-P. et al. 2012) [25]	Mage Filtering
(Revathi P and Hemalatha M. 2013) [27]	Noise Removal
(Arivazhagan S. et al. 2012) [28]	Transformation of RGB to HSI
(Zhou R. et al. 2013) [29]	Color Transformation
(Fadzil W.M.N.W.M. et al. 2014) [31]	Histogram Equalization, Intensity Adjustment, and Filtering methods like Median, Gaussian, and Disc Filter
(Hitimana E and Gwun O. 2014) [32]	Background Removal
(Oberti R. et al. 2014) [33]	Data Filtering
(Ranjan M. et al. 2015) [35]	Noise Removal
(Bhange M. A and Hingoliwala H. A. 2015) [36]	Image Resizing
(Warne P. P. and Ganorkar S. R. 2015) [37]	Histogram Equalization
(Mokhtar U. et al. 2015) [38]	Thresholding, Clustering, and Edge Detection
(Karmokar B. C. et al. 2015) [39]	Normalization
(Hanifa A. et al. 2015) [40]	Texture Processing
(Nemishte, D. et al. 2016) [41]	Transformation of images into HSV
(Mondal D and Kole D. K. 2016) [42]	Image Transformation
(Wang, Y. S. X and Zhang, S. 2016) [44]	Image Transformation
(Sladojevic S. et al. 2016) [45]	Cropping
(Qin F. et al. 2016) [46]	Color Transformation
(Padhy J. B. et al. 2016) [47]	Image Clipping and Image Smoothing
(Xie C. and He Y. 2016) [48]	Gray Scale Conversion
(Chant, C. D. et al. 2017) [49]	Image Cropping
(Prashar K. et al. 2017) [51]	Image Rotation and Brightness Adjustment
(Ashqar B. A. M. and Abu-Naser S. S. 2018) [53]	Image Resizing

(Veeraballi R. K. et al. 2020) [54]	Scaling
(Maa J. et al. 2018) [55]	Affine Transformations, Image Rotation, Random Crop and Jittering
(Wanga Z. and Zhang, S. 2018) [56]	Translation, Rotation, Scaling, and Color Jitter
(Ozguven M. M. and Adem K. 2019) [57]	Intensity Disturbance, Horizontal flips, Rotation Transformations, and Vertical Flips
(Singh V. 2019) [59]	Median Filtering
(Wu Q. et al. 2019) [60]	Flipping, Zooming, and Resizing the Images
(Azadbakht M. et al. 2019) [62]	Spectral Transformation
(Rashid J. et al. 2021) [63]	Scale Transformation
(Atila Ü. et al. 2019) [64]	Color Thresholding

2.2 Segmentation Techniques

Image segmentation techniques are used to segment the image region into various parts to reduce the complexity. The segmentation process is additionally used for separating the foreground from the background by assembling the pixel coefficients in the image based on color and shape similarities. In PLD detection models, the segmentation approach can easily differentiate the diseased part and thenormal part. From 2012 to 2022, the most widely adopted image segmentation approaches for detecting PLD are based on thresholding, clustering, and deep learning approaches.

Thresholding-based image segmentation: Thresholding techniques assisted in differentiating the affected parts and the healthy parts from the collected leaf images. The thresholding-based segmentation approaches initially fixed an appropriate threshold value and then applied a correlation factor for compensating the pixel modifications in the healthy part of the leaves. The authors Ranjan *et al.* (Ranjan M. et al. 2015) [35], Vipinadas and Thamizharasi (Vipinadas M.J and Thamizharasi A. 2016) [43], Warne and Ganorkar (Warne P. P and Ganorkar S. R. 2015) [37] and Singh *et al.* (Singh, A. et al. 2021) [73] utilized a thresholding-based PLD segmentation approach over various plant leaf images. Kapur's thresholding (Singh V. 2019) [59] and morphological-based thresholding (Kaur P. et al. 2022) [14] techniques are also used to improve the segmentation performance.

Numerous workshave been implemented with Principle Component Analysis (PCA)-based segmentation, (Arivazhagan S. et al. 2012) [28], (Hitimana E and Gwun O. 2014) [32], patch-based segmentation (Chen J. et al. 2022) [11] and also SSD-based segmentation (Mokhtar U. et al. 2015) [38] over the detection of PLD.

Clustering-based segmentation:In theclustering-based image segmentation approach, similar data points of the nearest pixels are grouped to form the cluster. While using these clusters, the affected and the unaffected portions of the leaves can be effectively identified. The techniques like K-Means Clustering (Amin H. et al. 2022) [7], (Moussafir M. et al. 2022) [6], (Suresh & Seetharaman, K. 2022) [17], (Pradhan, P. et al. 2022) [18], (Prasad, S. et al. 2012) [21], (Samanta D and Ghosh, A. 2012) [24], (Mondal D and Kole D. K. 2016) [42] and Fuzzy C-Means algorithm (Gunisetti L. et al. 2022) [15] (Prashar K. et al. 2017) [51] are offered the best results in leaf image segmentation process.

Deep learning-based segmentation: Deep learning-based leaf image segmentation models provide better results and also help to enhance the accuracy of PLD classification through effective segmentation. U-net-based segmentation models (Padhy J. B. et al. 2016) [47], (Jeon W.-S and Rhee S.-Y. 2017) [50] effectively encode the feature maps, ResNet, MobileNet (Wu Q. et al. 2019) [60] network provide better segmentation results and Yolov5 (Jiang P. et al. 2019b) [58] network is utilized to provide instance segmentation results. The categorization of leaf disease segmentation approaches is given in Fig. 4.

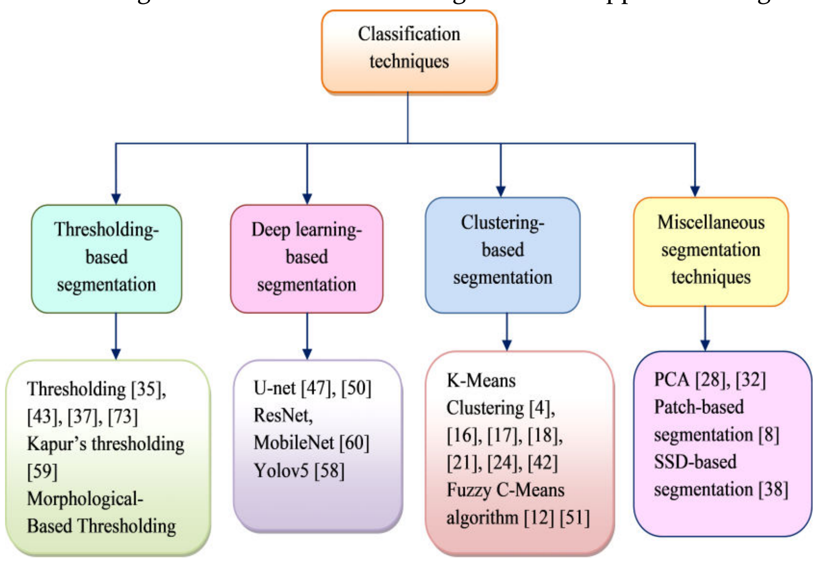


Figure 4. Conventional Segmentation-based methods used for the identification of PLD

2.3 Feature Extraction Techniques

Feature extraction is an important step in the PLD classification frameworks in providing high accuracy. The features are extracted from the diseased region based on the color, shape, and texture features. The feature extraction methods are excellent in providing better skewness, contrast, correlation, and color co-occurrence to the images. Gray level Co-occurrence Matrix (GLCM) is the statistical approach used for retrieving features from the images by calculating the spatial relationship among the pixels. Support Vector Machine (SVM) and PCA techniques aid in maximizing the margin between the class boundary and training data. The following Table 2 shows the different feature extraction techniques used for extracting the features from the plant leaves.

Table 2. Feature extraction methods used for the conventional PLDdetection models

Citation number	Feature extraction Techniques
(Prasad, S. et al. 2012) [21]	Gabor Wavelet Transform
(Gurjar A. A and Gulhane V. A. 2012) [22]	Scatter Matrix Decomposition
(Jing-Cheng Z. et al. 2012) [23]	Continuous Wavelet Analysis
(Samanta D and Ghosh, A. 2012) [24]	Histogram
(Aji A. F. et al. 2013) [26]	Pattern Recognition
(Revathi P and Hemalatha M. 2013) [27]	SVM
(Arivazhagan S. et al. 2012) [28]	Thresholding-based Masking

(Zhou R. et al. 2013) [29]	Xy-Color Histogram
(Al-Tarawneh, M. S. 2013) [30]	Image Enhancement
(Hitimana E and Gwun O. 2014) [32]	LUT-Based Gamma Correction Algorithm
(Zhang Z. et al. 2014) [34]	HSI Transformation
(Ranjan M. et al. 2015) [35]	Conversion Of RGB into HSI
(Bhange M. A and Hingoliwala H. A. 2015) [36]	Morphology-Based Feature Extraction
(Warne P. P. and Ganorkar S. R. 2015) [37]	Contrast Enhancement
(Mokhtar U. et al. 2015) [38]	Region Extraction
(Karmokar B. C. et al. 2015) [39]	NCL Algorithm
(Hanifa A. et al. 2015) [40]	Discrete Wavelet Decomposition
(Nemishte, D. et al. 2016) [41]	Color map
(Mondal D and Kole D. K. 2016) [42]	GLCM
(Vipinadas M.J and Thamizharasi A. 2016) [43]	GLCM
(Wang, Y. S. X and Zhang, S. 2016) [44]	Color Space Conversion
(Sladojevic S. et al. 2016) [45]	Affine Transformations
(Qin F. et al. 2016) [46]	Translation, Rotation, and Scaling.
(Padhy J. B. et al. 2016) [47]	Image Transformation
(Xie C. and He Y. 2016) [48]	GLCM
(Chant, C. D. et al. 2017) [49]	Binarization
(Jeon W.-S and Rhee S.-Y. 2017) [50]	Scale Invariant Feature Transform and Histogram of Oriented Gradients
(Prashar K. et al. 2017) [51]	Scale Invariant Feature Transform
(Veeraballi R. K. et al. 2020) [54]	Shading, Shape, and Surface
(Maa J. et al. 2018) [55]	PCA
(Singh V. 2019) [59]	Texture Feature Extraction
(Azadbakht M. et al. 2019) [62]	GLCM
(Rashid J. et al. 2021) [63]	Shear Transformation

2.4 Classification using Machine Learning and Deep Learning

The image classification is the final stage of thePLD detection model. Numerous models based on deep learning and machine learning are employed for PLD classification to provide highly accurate results. The conventional classification techniques provide many benefits in reducing the complexities based on time and computation, improved robustness, sensitivity, and specificity, and also support in reducingerrors. The categorization of the PLD classification models is represented in Fig. 5.

Determiningthe healthy leaf from the collected leaf images are very difficult task because the appearance of the leaf is slightly changed every day. Several PLD detection approaches are implemented under real conditions and uncontrolled conditions. These techniques investigate the specific vegetation indexes based on pattern analysis like Eigen feature regularization (Sunil C. K. et al. 2022) [3] and thresholding-based classification algorithm (Nawaz M. et al. 2022a) [16]. However, such models provide several issues like deployment cost, processing time, weather conditions, and real-time diagnostic capabilities. These issues may reduce the efficiency of the PLD detection models. So, several machine learning-based models have been developed to overcome the issues mentioned above.

SVM:SVM is a machine learning method that may classify data, such as normal or damaged leaves. It operates by determining the optimum way to separate distinct types of data and it is mainly adopted for classification purposes. It can discover the optimal hyperplane within a shorter period to provide potential significance over classification while creating the features based on pattern separation. In this survey, the research works like (Chen J. et al. 2022) [11], (Dwivedi R. et al. 2022) [12], (Moussafir M. et al. 2022) [6], (Pradhan, P. et al. 2022) [18], (Prasad, S. et al. 2012) [21], (Fadzil W.M.N.W.M. et al. 2014) [31] and (Mondal D and Kole D. K. 2016) [42] are used SVM-based leaf disease classification models to offer best results over the classification of PLD based on sugar beet plants, beans plants, pomegranate plant, tomato plant grape plant, maize, and wheat plants.

Regression techniques: These regression-based systemsare centered around machine learning techniques, which effectively detect the abnormalities in the leaves by eliminating the background and the occlusion. Regression models are better suited to tasks such as determining crop production or growth of plants depending on a variety of parameters. Using particular features, it can distinguish leaves as either good or bad. Logistic regression-based PLD detection models like (Zeng Q. et al. 2020) [5] and (Aji A. F. et al. 2013) [26] have been effectively solving the generalization problems with high accuracy.

Clustering-based classification techniques: Clustering techniques gather together comparable points of information depending on their qualities. Such algorithms can find trends and cluster comparable leaves together when used in the context of PLD identification. This method is very beneficial when dealing with unstructured data and attempting to find trends or new forms of diseases**.** The clustering-based PLD classification model used K-means clustering (Reddy S. R. G. et al. 2022) [13] and fuzzy c-means clustering (Gurjar A. A and Gulhane V. A. 2012) [22]. Here, the clusters are initially formed and then the clustering-based classification algorithm is applied to the clustered regions. These algorithms provide better leaf disease classification results in detecting the plant leaves.

Artificial Neural Networks (ANN)-based PLD detection: ANN is an attractive trainable machine learning model employed for object recognition. It is capable of learning complicated patterns and correlations in data, which makes it suitable for tasks such as image identification. ANNs may be trained on a huge dataset of annotated leaf photos to classify leaves either normal or sick according to their visual properties in connection with PLD detection. These models easily handle the complex task while processing the images with high accuracy. Hence, these techniques are mainly adopted for the identification and classification of PLD. Techniques like Deep Neural Networks (DNN) (Kuana C.-P. et al. 2012) [25], ANN (Albattah W. et al. 2022) [2], NN (Mahato D. K. et al. 2022) [4] and (Gajjar, R. et al. 2022) [19], Adaptive NN (Mustafa, H. et al. 2022) [20] and Deep Forward Neural Networks (DFNN) have been utilized for PLD detection purpose to produce higher classification accuracy and sensitivity with less execution time.

K-Nearest Neighbor (KNN): K-NN (Arivazhagan S. et al. 2012) [28] and (Azadbakht M. et al. 2019) [62]-based machine learning algorithmsare implemented for the detection and classification of PLD. During the detection process, it stores the trained dataand learns the parameters from the images. Therefore, the time required for training the ANN model is better than SVM. Moreover, the efficiency of the KNN-based leaf disease detection approaches is high.

Convolutional Neural Networks (CNN):The deep learning-based CNN models perform better in the classification of PLD. It providesgreater performance in terms of recognition accuracy than the pattern recognition methods. CNNs perform well in recognizing image tasks. They are built to continually acquire and retrieve information from images, therefore being ideal for assessing leaf images for identifying illnesses. It is an extremely effective instrument in the practical application of plant disease. Various CNN-based approaches used for PLD classification are (Zhou R. et al. 2013) [29], (Al-Tarawneh, M. S. 2013) [30], (Oberti R. et al. 2014) [533], (Zhang Z. et al. 2014) [34], (Vipinadas M.J and Thamizharasi A. 2016) [43], (Chant, C. D. et al. 2017) [49], (Liu B. et al. 2017) [52], (Ashqar B. A. M. and Abu-Naser S. S. 2018) [53], (Veeraballi R. K. et al. 2020) [54], (Singh V. 2019) [59], (Azadbakht M. et al. 2019) [62] and (Zhou C. et al. 2020) [65]. Furthermore, several CNN-based approaches used feature extraction techniques to increase classification accuracy and they are Deep CNN (DCNN)-based approaches (Fadzil W.M.N.W.M. et al. 2014) [31] and (Sladojevic S. et al. 2016) [45]. These techniques effectively learn the hidden parameters from the collected leaf images. R-CNN-based PLD detection technique (Warne P. P. and Ganorkar S. R. 2015) [37] is employed to resolve the overfitting problems.

The expanded version of CNN techniques provides more performance over the leaf disease detection and classification approaches. These includes AlexNet, Google Net (Oberti R. et al. 2014) [33], EfficientNet (Wang, Y. S. X and Zhang, S. 2016) [44] and (Jeon W.-S and Rhee S.-Y. 2017) [50], MobileNet (Qin F. et al. 2016) [46], Residual denseNet (Sladojevic S. et al. 2016) [45], GoogLeNet, SqueezeNet-MOD1, ResNet-50, AlexNet, SqueezeNet, and SqueezeNet-MOD2 (Xie C. and He Y. 2016) [48], AlexNet, VGG16, VGG19, ResNet50, ResNet101and InceptionV3 (Maa J. et al. 2018) [55], Yolov5 (Ozguven M. M. and Adem K. 2019) [57], DenseNet and MobileNet (Wanga Z. and Zhang, S. 2018) [56], ResNet34 (Jiang P. et al. 2019b) [58], transfer learning (Wu Q. et al. 2019) [60] and Inception-v3ShuffleNet-v2, EfficentNet-B6,VGG-16, , ResNet-50, DenseNet-121, and MobileNetV3 (Emebo O. et al. 2019) [61]. These provide better classification accuracy over the detection of leaf diseases with less processing time.

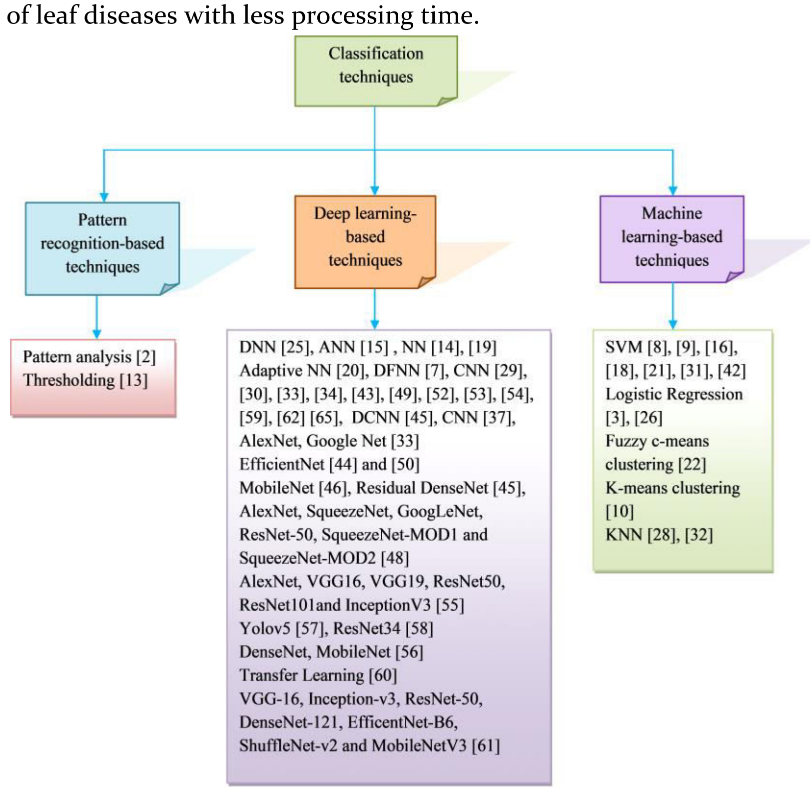


Figure 5. Classification methods used for PLDdetection from conventional research works

3. Disease classification details and performance measures concentrated on different PLD detection models

3.1 Datasets Link and Types of Plants

The sample leaf images collected from various standard databases and their types are given in below Table 3. Numerous investigators prepare databases for the usage of PLD identification models and most of them employ theplant village dataset and the Kaggle dataset for the PLD identification model. The plant leaves used for performing the PLD detection model are apples, tomatoes, potatoes, cotton, maize, tea, wheat, and so on. The image processing techniques adopted for the PLD mostly use the plant village dataset because it contains every type of leaf sample image.

Table 3. Datasets related to the type of plants for the detection of PLD

Citation number	Dataset description	Type of Plants
(Prasad, S. et al. 2012) [21]	Self-Prepared Home Dataset	Tomato, Apple, Potato and Groundnut
(Gurjar A. A and Gulhane V. A. 2012) [22]	Real World Dataset	Cotton
(Jing-Cheng Z. et al. 2012) [23]	Beijing Academy of Agriculture and Forestry Sciences, China	Wheat
(Samanta D and Ghosh, A. 2012) [24]	Real World Dataset	Maize
(Kuana C.-P. et al. 2012) [25]	Promega Corporation, Madison, Usa	Melon and Squash Plants
(Aji A. F. et al. 2013) [26]	Real World Dataset	Palm Tree
(Revathi P and Hemalatha M. 2013) [27]	Real World Dataset	Cotton Leaf
(Arivazhagan S. et al. 2012) [28]	Real-Time Dataset	Jackfruit, Potato, Tomato, Lemon, Banana, Beans, Mango, and Sapota
(Zhou R. et al. 2013) [29]	Nippon Beet Sugar Manufacturing Co., Ltd., Japan	Sugar Beet Plants
(Al-Tarawneh, M. S. 2013) [30]	-	Olive
(Fadzil W.M.N.W.M. et al. 2014) [31]	Digitally Captured By Using Digital Camera.	Orchid
(Hitimana E and Gwun O. 2014) [32]	Real-Time Dataset	Coffee Leaf
(Oberti R. et al.	Real-Time Dataset	Grapevine Leaves

2014) [33]		
(Zhang Z. et al. 2014) [34]	Hebei Agricultural University	Maize
(Ranjan M. et al. 2015) [35]	Database of Diseased Cotton Leaf	Cotton Leaves
(Bhange M. A and Hingoliwala H. A. 2015) [36]	Diseased And Non-Diseased Pomegranate Leaf Images	Pomegranate Leaf.
(Warne P. P and Ganorkar S. R. 2015) [37]	Dr. Punjabrao Krishi Vidyapith, Akola	Cotton Leaves
(Mokhtar U. et al. 2015) [38]	Real-Time Dataset	Tomato Leaf
(Karmokar B. C. et al. 2015) [39]	-	Tea Leaf
(Hanifa A. et al. 2015) [40]	Tea Leaf Pictures from Public Dataset	Tea Leaf
(Nemishte, D. et al. 2016) [41]	Real-Time Dataset	Grape Leaf
(Mondal D and Kole D. K. 2016) [42]	Real-Time Dataset	Wheat Leaf
(Vipinadas M.J and Thamizharasi A. 2016) [43]	Chirayikeezhu Agricultural Farm	Banana Leaf
(Wang, Y. S. X and Zhang, S. 2016) [44]	A Disease Leaf Image Database-IOT	Cucumber Leaf
(Sladojevic S. et al. 2016) [45]	New Plant Disease Image Database	Peach, Pair, Grapevine and Apple
(Qin F. et al. 2016) [46]	.Lang-Fang Forage Experimental Base	Alfalfa Leaf
(Padhy J. B. et al. 2016) [47]	-	Multiple Plants
(Xie C. and He Y. 2016) [48]	Hangqie I Eggplants	Eggplant Leaves
(Chant, C. D. et al. 2017) [49]	(Http://Bisque.Iplantcollaborative.Org)	Maize Leaves
(Jeon W.-S and Rhee S.-Y. 2017) [50]	Flavia Dataset	Bloom or Bear
(Prashar K. et al. 2017) [51]	Real-Time Dataset	Cotton Leaf
(Liu B. et al. 2017) [52]	Gansu Province, Qingyang County, China and Shanxi Province, Baishui County, China	Apple Leaf

(Ashqar B. A. M. and Abu-Naser S. S. 2018) [53]	Public Dataset Of 9000 Images	Tomato Leaf
(Veeraballi R. K. et al. 2020) [54]	Public dataset	Papaya Leaf
(Maa J. et al. 2018) [55]	.Https://Www.Forestryimages.Org/), Https://Plantvillage.Org/. F	Cucumber
(Wanga Z. and Zhang, S. 2018) [56]	Agricultural Science Institute Of Baoji City	Corn Leaf
(Ozguven M. M. and Adem K. 2019) [57]	Real-world dataset	Sugar Beet
(Jiang P. et al. 2019b) [58]	Apple Leaf Disease Dataset (ALDD)	Apple Leaf
(Singh V. 2019) [59]	Real-time dataset	Sunflower Leaf
(Wu Q. et al. 2019) [60]	Jiusan Farm, Nenjiang Farm, and Xiangyang Farm Of Northeast Agricultural University In Heilongjiang Province	Soybean
(Emebo O. et al. 2019) [61]	Plant village.Org	Tomato Leaf
(Azadbakht M. et al. 2019) [62]	Moghan Fertilized Plain,	Wheat Leaf
(Rashid J. et al. 2021) [63]	Plant village dataset	Potato Leaf
(Atila Ü. et al. 2019) [64]	Plant Village dataset	Grape, Cherry, Tomato, Apple and Peach
(Zhou C. et al. 2020) [65]	AI CHALLENGER	Tomato Leaf

3.2 Binary Vs Multiple Classification

Fig. 6 depicts the analysis of detected and classified diseases by the conventional PLD detection methodologies. Late and Early Blight from potato plant are detected by (Zhao Y. et al. 2022) [1], fungal disease, leaf crumple and red spot from cotton are classified by (Sunil C. K. et al. 2022) [3], Hawar leaf diseases, anthracnose diseases, and purple spot from palm plant are detected by (Jiang P. et al. 2019a) [9], fungal, yellow spots, bacterial, late scorch, early scorch, and brown spots diseases are detected by (Chen J. et al. 2022) [11], black leaf spot and sun scorch are detected by (Kaur P. et al. 2022) [14], brown spot, Grey speck disease, and leaf blight are identified by (Mahato D. K. et al. 2022) [1], red for Bacterial blight, green for Fussarium wilt, blue for Reddning and black for cotton rust are detected by (Albattah W. et al. 2022) [2], (Maa J. et al. 2018) [55], bacterial disease, fungal disease and virul disease are detected by (Moussafir M. et al. 2022) [6], (Suresh & Seetharaman, K. 2022) [17], (Arivazhagan S. et al. 2012) [28], (Chant, C. D. et al. 2017) [49] and (Pradhan, P. et al. 2022) [18] from cotton and pomegranate leaves, Late scorch, Early Scorch, tiny whiteness, Ashen Mold Cottony mold are identified by (Prasad, S. et al. 2012) [21] from grape leaves,

.porosity, mites, powdery mildew, gray leaf spot, Gymnosporangiumsabinae, wilt, downy mildew Taphrina deformans, Erwinia amylovora, Venturia, and Rust by (Kuana C.-P. et al. 2012) [25] from grape and peach, alfalfa common leaf spot, alfalfa rust, Leptosphaerulina leaf spot by (Aji A. F. et al. 2013) [26] from alfalfa leaf, Leaf Curl, Bacterial Blight and Alternaria Leaf Spot from cotton leaf by (Fadzil W.M.N.W.M. et al. 2014) [31], Brown spot, Rust, Mosaic, and Alternaria leaf spot by (Hitimana E and Gwun O. 2014) [32] from apple plant, Bacterial Spot, Septorial Leaf Spot, Yellow Early Blight, Leaf mold, Leaf Curl Virus by (Oberti R. et al. 2014) [33] from powdery mildew, tomato plant, anthracnose, downy mildew, and target leaf spots by (Ranjan M. et al. 2015) [35] from cucumber plant, papaya mosaic and leaf Curl of Papaya by (Zhang Z. et al. 2014) [34] from papaya plants. Moreover, streak disease, small spot disease, corn leaf spot, and leaf spot disease, brown spot disease, round spot disease by (Bhange M. A and Hingoliwala H. A. 2015) [36] from corn leaves, Grey spot, Alternaria leaf spot, Mosaic, Brown spot, and Rust by (Warne P. P and Ganorkar S. R. 2015) [37] from apple leaf, black spot, downy mildew, and bacterial leaf spot by (Karmokar B. C. et al. 2015) [39] from sunflower leaf, septoria leaf spot and mosaic diseases by (Nemishte, D. et al. 2016) [41], (Rashid J. et al. 2021) [63]from tomato leaf, early and late blight by (Vipinadas M.J and Thamizharasi A. 2016) [43] from potato leaf, Cassava Brown Steak Disease (CBSD), Cassava Green Mite (CGM), Cassava Mosaic Disease (CMD), and Cassava Bacterial Blight (CBB), by (Qin F. et al. 2016) [46] from cassava leaf, early blight, bacterial spot, target spot, septoria leaf spot, two-spotted spider mite, leaf mold, late mosaic virus, bright mold, by (Jeon W.-S and Rhee S.-Y. 2017) [50] from multiple leaves, corn common rust, apple black rot, apple scab, and grape leaf blight from multiple leaves by (Liu B. et al. 2017) [52], Sheat Blight (SB), Rice Blast (RB), and Bacterial Leaf Blight (BLB) by (Veeraballi R. K. et al. 2020) [54] from rice plants, bacterial blight, leaf spot, target spot, nutrient deficiency, powdery mildew, leaf curl (Maa J. et al. 2018) [55] from cotton leaves, downy mildew, Phoma blight, Alternaria leaf blight, and Verticillium wilt (Wanga Z. and Zhang, S. 2018) [56] from sunflower, yellow leaf, leaf spot, septoria, mosiac virus, bacterial spot, leaf blight, leaf mould, and early blight from tomato by (Singh V. 2019) [59], leaf rust, powdery mildew, and stripe rust from wheat (Wu Q. et al. 2019) [60], (Emebo O. et al. 2019) [61] detects North leaf blight, gray leaf spot, and common rust from corn, (Zhou C. et al. 2020) [65] CMD and CBB from cassava leaves.

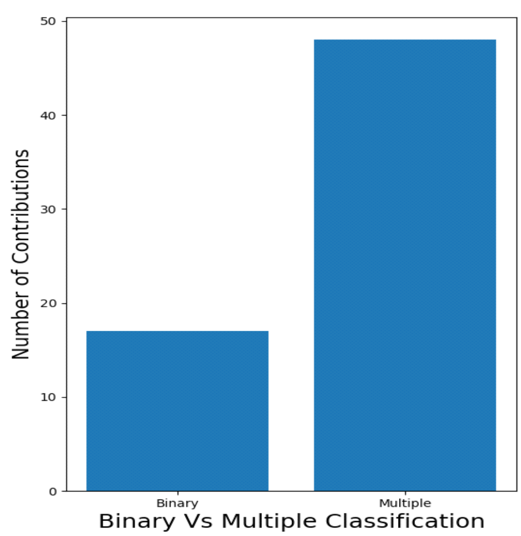


Figure 6. Analysis of Binary vs. multiple classification of leaf diseases from the existing models

3.3 Performance Metrics

The validation measures used in performing the traditional PLD detection models are shown in Table 4. In Table 4, 96% of the models used accuracy measure, 30.77% of models used precision, 27.69% of models employed f1-Score, and 22.34% of frameworks utilized recall for presenting the PLD detection processes.Moreover, several models used computation time and error rate measures for the detection purpose.

Table 4. Performance measures utilized for the detection and classification of PLD over recent years

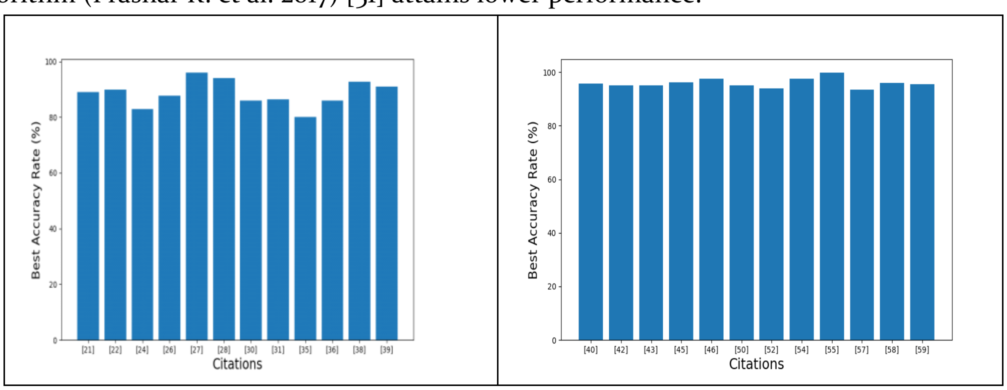
Citation	Accuracy	Precision	F1-measure	Recall	Miscellaneous measures
(Prasad, S. et al. 2012) [21]	✓	-	-	-	-
(Gurjar A. A and Gulhane V. A. 2012)	✓	-	-	-	-
(Jing-Cheng Z. et al. 2012) [23]	✓	-	-	-	-
(Samanta D and Ghosh, A. 2012) [24]	✓	-	-	-	-
(Kuana C.-P. et al. 2012) [25]	✓	-	-	-	Error rate and execution time
(Aji A. F. et al. 2013) [26]	✓	-	-	-	-
(Revathi P and Hemalatha M. 2013) [27]	✓	-	-	-	-
(Arivazhagan S. et al. 2012) [28]	✓	-	-	-	-
(Zhou R. et al. 2013) [29]	✓	✓	✓	✓	-
(Al-Tarawneh, M. S. 2013) [30]	✓	-	-	-	Training time
(Fadzil W.M.N.W.M. et al. 2014) [31]	✓	-	-	-	-
(Hitimana E and Gwun O. 2014) [32]	✓	-	-	-	Sensitivity and specificity
(Oberti R. et al. 2014) [33]	✓	✓	✓	✓	-
(Zhang Z. et al. 2014) [34]	✓	-	-	-	-
(Ranjan M. et al. 2015) [35]	✓	-	-	-	-
(Bhange M. A and Hingoliwala H. A. 2015) [36]	✓	-	-	-	-

(Warne P. P and Ganorkar S. R. 2015) [37]	✓	✓	✓	-	Sensitivity
(Mokhtar U. et al. 2015) [38]	✓	-	-	-	-
(Karmokar B. C. et al. 2015) [39]	✓	-	-	-	Kappa coefficient
(Hanifa A. et al. 2015) [40]	✓	✓	✓	✓	-
(Nemishte, D. et al. 2016) [41]	✓	✓	✓	✓	Sensitivity and specificity
(Mondal D and Kole D. K. 2016) [42]	✓	-	-	-	-
(Vipinadas M.J and Thamizharasi A. 2016) [43]	✓	-	-	-	-
(Wang, Y. S. X and Zhang, S. 2016) [44]	✓	✓	✓	✓	Sensitivity, specificity, AUC, CAR, FPR and TPR
(Sladojevic S. et al. 2016) [45]	✓	✓	✓	✓	Sensitivity and computation time
(Qin F. et al. 2016) [46]	-	-	-	-	Specificity, dice coefficient, and jacard index
(Padhy J. B. et al. 2016) [47]	✓	-	-	-	-
(Xie C. and He Y. 2016) [48]	✓	-	-	-	-
(Chant, C. D. et al. 2017) [49]	✓	✓	✓	✓	-
(Jeon W.-S and Rhee S.-Y. 2017) [50]	✓	-	-	-	-
(Prashar K. et al. 2017) [51]	✓	✓	✓	✓	Sensitivity and specificity
(Liu B. et al. 2017) [52]	✓	-	-	-	-
(Ashqar B. A. M. and Abu-Naser S. S. 2018) [53]	-	✓	-	✓	-
(Veeraballi R. K. et al. 2020) [54]	✓	-	-	-	mAP
(Maa J. et al. 2018) [55]	✓	✓	✓	✓	Kappa
(Wanga Z. and Zhang, S. 2018) [56]	✓	-	-	-	-
(Ozguven M. M. and	✓	-	-	-	-

Adem K. 2019) [57]					
(Jiang P. et al. 2019b) [58]	✓	-	-	-	Sensitivity and specificity
(Singh V. 2019) [59]	✓	-	-	-	-
(Wu Q. et al. 2019) [60]	✓	✓	✓	✓	-
(Emebo O. et al. 2019) [61]	-	✓	✓	✓	-
(Azadbakht M. et al. 2019) [62]	✓	-	-	-	AUC
(Rashid J. et al. 2021) [63]	✓	-	-	-	-
(Atila Ü. et al. 2019) [64]	✓	-	-	-	-
(Zhou C. et al. 2020) [65]	✓	✓	✓	✓	-

3.4 Best Recorded Performance in terms of AccuracyAnalysis of accuracy, precision, recall metrics for the conventional PLD detection approaches

The accuracy-based performance of the conventional PLDdetection models has been surveyed and provided as the graphical view in Fig. 7, 8 and 9. From Fig 7, theCNN-based model attained the best accuracy of 99.84% (Oberti R. et al. 2014) [33], 99% by DCNN (Nemishte, D. et al. 2016) [41], 99.11% by trasnsfer learning (Wu Q. et al. 2019) [60], 99.39% by efficientNet (Wang, Y. S. X and Zhang, S. 2016) [44] and 99% by logistic regression (Prashar K. et al. 2017) [51]. Accordingly, the figure 8 shows the elevated precision rate of the baseline PDL detection techniques. While considering Fig 8, the ResNet 101 and Inception V_3 model Maa J. et al. (2018) [55] attains 98.2% precision rate. Here, the 55^{th} and 60^{th} reference attains equivalent performance. At the same time, the Adaptive Neuro fuzzy approach (Hanifa A. et al. 2015) [40] attains lower performance. While taking Fig 9, it shows the better recall rates. Here, the transfer learning model achieves elevated recall rate which is much better than the other baseline approaches. Consequently, the Fuzzy C-Means algorithm (Prashar K. et al. 2017) [51] attains lower performance.



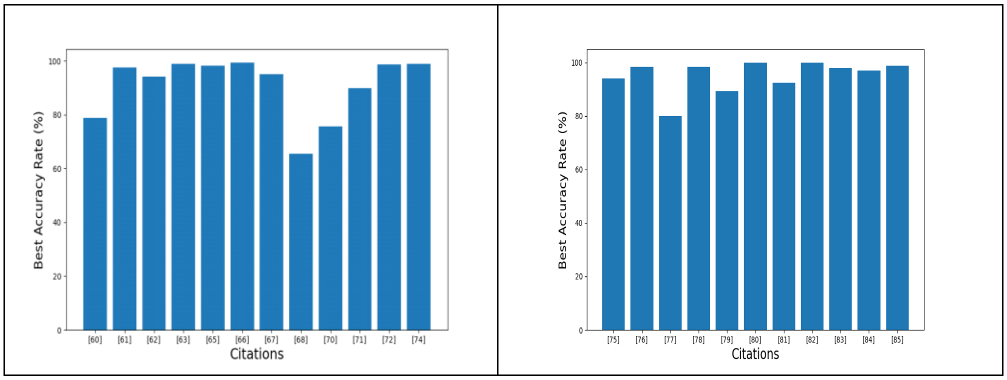


Figure 7. Best recorded accuracy values of the existing PLDdetection models

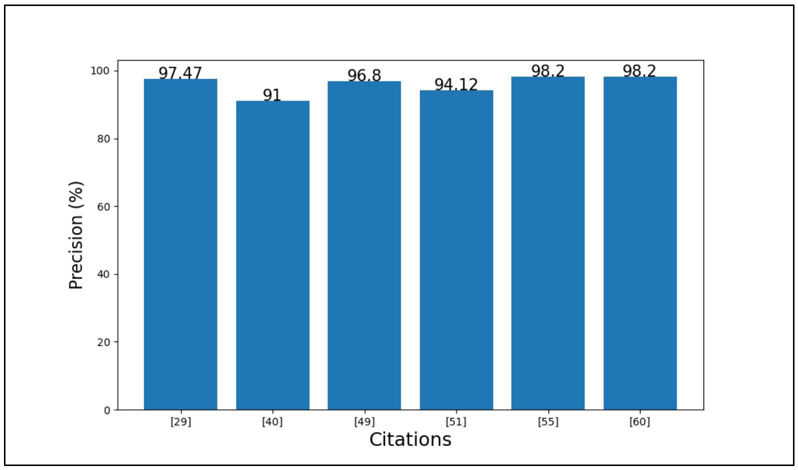


Figure 8. Best recorded precision values of the existing PLDdetection models

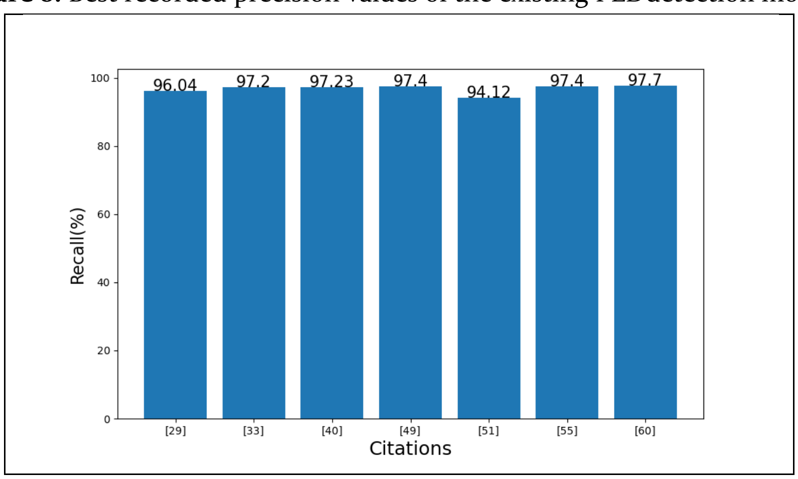


Figure 9. Best recorded recall values of the existing PLDdetection models

4. Research Gaps and challenges

The conventional PLD detection approaches utilize pattern analysis for the classification of PLDs, these approaches are widely applicable to various types of plant leaves, and numerous diseases are extracted usingsuch techniques. Hence, several deep learningand machine learning-based approaches are developed to solve the challengespresent in detecting the PLD. The deep learning-based approaches decrease the processing time and improve the accuracy, sensitivity, and specificity.However, the researcher suffers several problems, such as extremely harsh operating circumstances. The images are taken under extremely low lighting and brightness settings and hence, these require edge detection, background removal, image resizing, reshaping, and histogram equalization, using these techniques to reduce the computation time. Hence, efficient image processing techniques are needed to give higher classification results over PLD. Moreover, certifiable applications are very difficult to authorize when the investigation relies upon a non-damaging way. Managing an increasingly prudent monitoring and upgrading plan is a crucial component of these approaches. Furthermore, some techniques are excessively explicit in the detection of PLD. Furthermore, several problemslike datasets with low representativeness, predisposition, overtraining, overfitting, and undersized datasets placed in uncontrolled environmental conditions. In addition, several leaf disease detection models do not provide adequate robustness and scalability. Further developments are needed to improve the feasibility and reliability of the deep learning-based PLD detection models. There is a possibility of incorrect classification of outcomes, though this problem could potentially be fixed in the future and the convergence rate will also be enhanced.

The severity level classification is mainly helpful for providing diagnostic treatment for plant leaf diseases. Hence, all the PLD detection techniques with severity level classification are important to improve the economic growth of farmers. By detecting leaf diseases in their early stages, farmers might potentially reduce plant mortality rates. This is because severe leaf diseases can completely kill a plant's growth rate. Hence, deep learning-based PLD classification approaches are developed with alarms for the detection of diseases at anearly stage. The previously used classification systems don't elaborate onhow the impact of the leaves under various types of plant leaf diseases and the classification. Hence, new systems are needed to overcome these challenges and provide an efficient classification of multiple diseases.

5. Conclusion

This survey aimed to provide an effective analysis of various types of PLD detection approaches based on deep learning and machine learning techniques. The collection of research works from the year 2012 to 2022 was considered for this survey. It provided detailed information about the utilization of datasets for detecting the PLDs, the types of plants to be analyzed, and the type of diseases detected using the traditional models. Furthermore, the tools used for the detection process, along with the best accuracy rates were analyzed. Moreover, the details about the preprocessing techniques, image acquisition, feature extraction process, image segmentation, and also the classification strategies used for the detection and classification of PLD were analyzed in this survey. Additionally, the research gaps and the challenges of the conventional PLD detection approaches were discussed. This survey paper provided strong information on the detection and classification of PLD that might be helpful for future research work. Additionally, the real time applications and the tools for using the detection of plant leaf disease will be taken as the upcoming works. The deep analysis of the hybrid and the ensemble approaches will be definitely be the part of our upcoming work.

References

1. Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., Zhang, Z. (2022). Plant Disease Detection Using Generated Leaves Based on DoubleGAN, *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, *19(3)*, 1817-1826.

2. Albattah, W., Nawaz, M., Javed, A., Masood, M &Albahli, S. (2022). A novel deep learning method for detection and classification of plant diseases, *Complex & Intelligent Systems*, 8, 507–524.
3. Sunil C. K., Jaidhar C. D and Patil, N. (2022). Cardamom Plant Disease Detection Approach Using EfficientNetV2, *IEEE Access*, *10*, 789-804.
4. Mahato, D. K., Pundir, A & Saxena, G. J. (2022). An Improved Deep Convolutional Neural Network for Image-Based Apple Plant Leaf Disease Detection and Identification, *Journal of The Institution of Engineers (India): Series*.
5. Zeng, Q., Ma, X., Cheng, B., Zhou, E and Pang, W. (2020). GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning, *inIEEE Access*, *8*, 172882-172891.
6. Moussafir, M., Chaibi, H., Saadane, R., Chehri, A., Rharras, A. E & Jeon, G. (2022). Design of efficient techniques for tomato leaf disease detection using genetic algorithm-based and deep neural networks, *Plant and Soil*, 479, 251–266.
7. Amin, H., Darwish, A., Hassanien, A. E and Soliman, M. (2022). End-to-End Deep Learning Model for Corn Leaf Disease Classification, *IEEE Access*, *10*, 31103-31115.
8. Saleem, M. H., Potgieter, J and Arif, K. M. (2022). A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand, *IEEE Access*, 10, 89798-89822.
9. Jiang, P., Chen, Y., Liu, B., He, D and Liang, C. (2019a). Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks, *IEEE Access*, *7*, 59069-59080.
10. Barburiceanu, S., Meza, S., Orza, B., Malutan, R and Terebes, R. (2021). Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture, *IEEE Access*, *9*, 160085-160103.
11. Chen, J., Chen, W., Zeb, A., Yang, S and Zhang, D. (2022). Lightweight Inception Networks for the Recognition and Detection of Rice Plant Diseases, *IEEE Sensors Journal, 22(14)*, 14628-14638.
12. Dwivedi, R., Dutta, T and Hu, Y. -C. (2022). A Leaf Disease Detection Mechanism Based on L1-Norm Minimization Extreme Learning Machine, *IEEE Geoscience and Remote Sensing Letters, 19*(8019905). 1-5.
13. Reddy, S. R. G., Varma, G. P. S & Davuluri, R. L. (2022). Deep Neural Network (DNN) Mechanism for Identification of Diseased and Healthy Plant Leaf Images Using Computer Vision, *Annals of Data Science*.
14. Kaur, P., Harnal, S., Gautam, V., Singh, M. P & Singh, S. P. (2022). A novel transfer deep learning method for detection and classification of plant leaf disease, *Journal of Ambient Intelligence and Humanized Computing*.
15. Gunisetti, L., Koduri, S. B & Jagannathan, V. (2022). Optimized deep learning system for smart maize leaf disease detection in IoT platform via routing algorithm, *Multimedia Tools and Applications*.
16. Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim J & Hussain, A. (2022b). A robust deep learning approach for tomato plant leaf disease localization and classifcation, *Scientifc Reports, 12(1),* 1-18.
17. Suresh & Seetharaman, K. (2022). Real-time automatic detection and classification of groundnut leaf disease using hybrid machine learning techniques, *Multimedia Tools and Applications*.

18. Pradhan, P., Kumar B. & Mohan, S. (2022). Comparison of various deep convolutional neural network models to discriminate apple leaf diseases using transfer learning, *Journal of Plant Diseases and Protection*, *129*, 1461–1473.
19. Gajjar, R., Gajjar, N., Thakor, V. J., Patel, N. P & S. Ruparelia, (2022). Real-time detection and identification of plant leaf diseases using convolutional neural networks on an embedded platform, *The Visual Computer, 38*, 2923–2938.
20. Mustafa, H., Umer, M., Hafeez, U., Hameed, A., Sohaib, A., Ullah S. & Madni, H. A. (2022). Pepper bell leaf disease detection and classification using optimized convolutional neural network, *Multimedia Tools and Applications*.
21. Prasad, S., Kumar, P., Hazra1, R and Kumar, A. (2012). Plant Leaf Disease Detection Using Gabor Wavelet Transform, *SEMCCO 2012, LNCS 7677*, 372–379.
22. Gurjar, A. A and Gulhane, V. A. (2012). Disease Detection On Cotton Leaves by Eigenfeature Regularization and Extraction Technique, *International Journal of Electronics, Communication & Soft Computing Science and Engineering (IJECSCSE), 1(1)*.
23. Jing-Cheng, Z., Lin, Y., Ji-Hua, W., Wen-Jiang, H., Li-Ping C. and Dong-Yan, Z. (2012). Spectroscopic Leaf Level Detection of Powdery Mildew for Winter Wheat Using Continuous Wavelet Analysis, *Journal of Integrative Agriculture, 11(9)*: 1474-1484.
24. Samanta, D and Ghosh, A. (2012). Histogram Approach for Detection of Maize Leaf Damage, *International Journal of Computer Science and Telecommunications*, *3(2)*.
25. Kuana, C.-P., Huanga, H.-C., Chang C.-C., Lu, Y.-L. (2012). TaqMan real-time PCR for detection and quantitation of squash leaf curl virus in cucurbits, *Journal of Virological Methods*, 179, 367–372.
26. Aji, A. F., Munajat, Q., Pratama, A., P., Kalamullah, H., Aprinaldi, A., Setiyawan, J. and Arymurthy, A. M. (2013). Detection of Palm Oil Leaf Disease with Image Processing and Neural Network Classification on Mobile Device, *International Journal of Computer Theory and Engineering, 5(3)*.
27. Revathi, P and Hemalatha, M. (2013). An Improved Cotton Leaf Spot Disease Detection using Proposed Classifiers, *International Journal of Engineering Research & Technology (IJERT), 2(12)*.
28. Arivazhagan, S., Shebiah, R. N., Ananthi, S., Varthini, S. V. (2012). Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features, *Agric Eng Int: CIGR Journal, 15*.
29. Zhou, R., Kaneko, S., Tanaka, F., Kayamori, M and Shimizu, M. (2013). Matching-Based Cercospora Leaf Spot Detection in Sugar Beet, *International Journal of Nutrition and Food Engineering, 7(7)*.
30. Al-Tarawneh, M. S. (2013). An Empirical Investigation of Olive Leave Spot Disease Using Auto-Cropping Segmentation and Fuzzy C-Means Classification, *World Applied Sciences Journal, 23(9)*, 1207-1211.
31. Fadzil W.M.N.W.M., Rizam M.S.B. S., Jailani, R., Nooritawati M.T., (2014). Orchid Leaf Disease Detection using Border Segmentation Techniques, *2014 IEEE Conference on Systems, Process and Control 12-14*.
32. Hitimana, E and Gwun, O. (2014). Automatic Estimation Of Live Coffeeleaf Infection Based On Image Processing Techniques.
33. Oberti, R., Marchi, M., Tirelli, P., Alcante, A., Iriti, M., Borghese, A. N. (2014). Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity, *Computers and Electronics in Agriculture, 104*, 1–8.

34. Zhang, Z., Li, Y., Wang, F and He, X. (2014). A Particle Swarm Optimization Algorithm for Neural Networks in Recognition of Maize Leaf Diseases, *Sensors & Transducers, 166(3)*, 181-189.
35. Ranjan, M., Weginwar, M. R., Joshi, N., Ingole, A.B. (2015). Detection And Classification Of Leaf Disease Using Artificial Neural Network, *International Journal of Technical Research and Applications, e 3(3)*, 331-333.
36. Bhange, M. A and Hingoliwala, H. A. (2015). Detection of Bacterial Blight on Pomegranate Leaf, *International Journal on Recent and Innovation Trends in Computing and Communication, 3(6)*,3682 - 3685.
37. Warne, P. P and Ganorkar, S. R. (2015). Detection of Diseases on Cotton Leaves Using K-Mean Clustering Method, *International Research Journal of Engineering and Technology (IRJET), 02(04)*.
38. Mokhtar, U., Ali, M.A.S., Hassanien, A. E and Hefny, H. (2015). Identifying Two of Tomatoes Leaf Viruses Using Support Vector Machine, *Advances in Intelligent Systems and Computing, 339*.
39. Karmokar, B. C., Ullah, M. S., Siddiquee K. and Alam, K. R. (2015). Tea Leaf Diseases Recognition using Neural Network Ensemble*, International Journal of Computer Applications, 114*, 0975 – 8887.
40. Hanifa, A., Billah, M., Miah, M. B. A., Amin, R. (2015). Adaptive Neuro Fuzzy Inference System based Tea Leaf Disease Recognition using Color Wavelet Features, *Communications on Applied Electronics (CAE), 3(5)*.
41. Nemishte, D., Patil, R., Udgave, S., More, S and Kasture, M. (2016). Grape Leaf Disease Detection Using K-means Clustering Algorithm, *International Research Journal of Engineering and Technology (IRJET)*, *03*.
42. Mondal, D and Kole, D. K. (2016). A Time Efficient Leaf Rust Disease Detection Technique of Wheat Leaf Images Using Pearson Correlation Coefficient and Rough Fuzzy C-Means, *Advances in Intelligent Systems and Computing, 433*.
43. Vipinadas. M.J., Thamizharasi, A. (2016). Banana Leaf Disease Identification Technique, *International Journal of Advanced Engineering Research and Science (IJAERS), 3(6)*.
44. Wang, Y. S. X., Zhang, S. (2016). Plant Disease Leaf Image Segmentation Using K-Means Clustering Based on Internet of Things, *International Journal of Research in Agricultural Sciences, 3(*2).
45. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D. and Stefanovic, D. (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification, *Hindawi Publishing Corporation Computational Intelligence and Neuroscience, 2016*(3289801).
46. Qin, F., Liu, D., Sun, B., Ruan, L., Ma, Z., Wang, H. (2016). Identification of Alfalfa Leaf Diseases Using Image Recognition Technology, *11(12)*.
47. Padhy, J. B., Kumar, D. D., Manish, L. and Choudhry, L. (2016). Leaf Disease Detection Using K-Means Clustering And Fuzzy Logic Classifier, *International journal of engineering studies and technical approach, 02(*5)
48. Xie, C. and He, Y. (2016). Spectrum and Image Texture Features Analysis for Early Blight Disease Detection on Eggplant Leaves, *Sensors*.
49. Chant, C. D., Wiesner-Hanks, T., Chen, S., Stewart, E. L., Yosinski, J., Gore, M. A., Nelson, R. J., Lipson, H. (2017). Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning, *phytopathology*.

50. Jeon, W.-S and Rhee, S.-Y. (2017). Plant Leaf Recognition Using a Convolution Neural Network, *International Journal of Fuzzy Logic and Intelligent Systems, 17(1)*, 26-34.
51. Prashar, K., Talwar, R., Kant, C., Pannu, P.P.S. (2017). A Novel Shape and Texture based Analysis of the American Cotton Leaf Diseases with SVM Classification, *Jour of Adv Research in Dynamical & Control Systems, 10(13)*.
52. Liu, B., Zhang, I.D. Y., He, D.J and Li, Y. (2017). Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks, *Symmetry, 10*, 11.
53. Ashqar, B. A. M., Abu-Naser, S. S. (2018). Image-Based Tomato Leaves Diseases Detection Using Deep Learning, *International Journal of Academic Engineering Research (IJAER), (12)*, 10-16.
54. Veeraballi, R. K., Nagugari, M. S., Annavarapu, C. S. R and Gownipuram, E. V. (2020). Deep Learning Based Approach for Classification and Detection of Papaya Leaf Diseases, *springer*, 291–302.
55. Maa, J., Dua, K., Zhenga, F., Zhangb, L., Gongc, Z., Suna, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network, *Computers and Electronics in Agriculture, 154*, 18–24.
56. Wanga, Z., Zhang, S. (2018). Segmentation of Corn Leaf Disease Based on Fully Convolution Neural Network, *Academic Journal of Computing & Information Science, 1(1)*: 9-18.
57. Ozguven, M. M., Adem, K. (2019). Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms, *Physica A: Statistical Mechanics and its Applications, 535*, 122537.
58. Jiang, P., Chen, Y., Liu, B., He, D and Liang, C. (2019b). Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks, *Special Section On Advanced Optical Imaging For Extreme Environments*.
59. Singh, A., Singh, A., Yadav, S., Sengar, N., Dutta, M. K. (2021). Identification of disease using deep learning and evaluation of bacteriosis in peach leaf, *Ecological Informatics, 61*, 101247.
60. Wu, Q., Zhang K. and Meng, J. (2019). Identification of Soybean Leaf Diseases via Deep Learning, *J. Inst. Eng. India Ser. A*.
61. Emebo, O., Fori, B., Victor G. and Zannu, T. (2019). Development of Tomato Septoria Leaf Spot and Tomato Mosaic Diseases Detection Device Using Raspberry Pi and Deep Convolutional Neural Networks, *IOP Conf. Series: Journal of Physics: Conf. Series 1299 012118*.
62. Azadbakht, M., Ashourloo, D., Aghighi, H., Radiom, S., Alimohammadi, A. (2019). Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques, *Computers and Electronics in Agriculture, 156*, 119–128.
63. Rashid, J., Khan, I., Ali, G., Almotiri, S. H and AlGhamdi, M. A and Masood, K. (2021). Multi-Level Deep Learning Model for Potato Leaf Disease Recognition, *Electronics, 10*, 2064.
64. Atila, Ü., Uçar, M., Akyol, K., Uçar, E. (2019). Plant leaf disease classification using EfficientNet deep learning model, *Ecological Informatics*.
65. Zhou, C., Zhou, S., Xing, J. and Song, J. (2020). Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network, *IEEE Acess, 9*.
66. Ayu, H. R., Surtono, A and Apriyanto, D. K. (2020). Deep learning for detection cassava leaf disease, *Journal of Physics: Conference Series, 1751*, 012072.

67. Abed, S. H., Al-Waisy, A. S., Mohammed, H. J and Al-Fahdawi, S. (2020). A modern deep learning framework in robot vision for automated bean leaves diseases detection, *International Journal of Intelligent Robotics and Applications, 5*, 235–251.
68. Shin, J., Chang, Y. K., Heung, B., Nguyen-Quang, T., Price, G. W and Al-Mallahi, A. (2020). A deep learning approach for RGB image-based powdery mildew disease detection on strawberry leaves, *Computers and Electronics in Agriculture, 183*, 106042.
69. Yadav, M. G., Nennuri, R., Rajeshwari, D., Rishitha V and Puneeth, T. (2021). Identification of Plant Leaf Diseases using Machine Learning Algorithms, *Annals of R.S.C.B., ISSN:1583-6258, 25(6)*, 6866-6875.
70. Chowdhury, M. E. H., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., Al-Emadi, N., Reaz, M. B. I., Islam, M. T and Ali, S. H. (2021). Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques, *AgriEngineering, 3*, 294–312.
71. Ramkumar, G., Amirthalakshmi T.M., Prabu, R. T., Sabarivani, A. (2021). An Effectual Plant Leaf Disease Detection using Deep Learning Network with IoT Strategies, *Annals of R.S.C.B., ISSN:1583-6258, 25(4)*, 8876 - 8885.
72. Ahmed A.A., Reddy G.H. (2021). A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning, *AgriEngineering, 3*, 478–493.
73. Singh, V. (2019). Sunflower leaf diseases detection using image segmentation based on particle swarm optimization, *Artificial Intelligence in Agriculture, 3*, 62-68.
74. Poornam, S., Devaraj, A. F. S. (2021). Image based Plant leaf disease detection using Deep learning, *International Journal of Computer communication and Informatics, 3(1)*.
75. Memon M.S., Kumar P., Iqbal R. (2022). Meta Deep Learn Leaf Disease Identification Model for Cotton Crop, *Computers, 11*, 102.
76. Malik, A., Vaidya, G., Jagota, S., Eswaran, A., Sirohi, I., Batra, M. Rakhra, and E. Asenso, (2022). Design and Evaluation of a Hybrid Technique for Detecting Sunflower Leaf Disease Using Deep Learning Approach, *Journal of Food Quality, (9211700),12*.
77. Jhatial, M. J., Shaikh, R. A., Shaikh, N. A., Rajper, S., Arain, R. H., Chandio, G. H. (2022). Abdul Qadir Bhangwar, Hidayatullah Shaikh, Kashif Hussain Shaikh, "*Deep Learning-Based Rice Leaf Diseases Detection Using Yolov5, IBA, 6(1*).
78. Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim, J & Hussain, A. (2022a). A robust deep learning approach for tomato plant leaf disease localization and classification, *Neurological science*.
79. Ashwinkumar, S., Rajagopal, S., Manimaran, V., Jegajothi, B. (2022). Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks, *Materials Today: Proceedings*.
80. Ma, Z., Wang, Y., Zhang, T., Wang, H., Jia, Y., Gao, R., Su, Z. (2022). Maize leaf disease identification using deep transfer convolutional neural networks, *Int J Agric & Biol Eng*.
81. Jiang J., Liu H., Zhao C., He C., Ma J., Cheng T., Zhu Y., Cao W., Yao X., (2022). Evaluation of Diverse Convolutional Neural Networks and Training Strategies for Wheat Leaf Disease Identification with Field-Acquired Photographs, *Remote Sens., 14*, 3446.
82. Noola, D. A., Basavaraju, D. R. (2022). Corn leaf image classification based on machine learning techniques for accurate leaf disease detection, *International Journal of Electrical and Computer Engineering (IJECE), 12(3)*, 2509~2516.

83. Chen, H.C., Widodo, A. M., Wisnujati, A., Rahaman, M., Lin, J. C.W., Chen, L and Weng, C.E. (2022). AlexNet Convolutional Neural Network for Disease Detectionand Classification of Tomato Leaf, *Electronics, 11*, 951.
84. Ksibi, A., Ayadi, M., Soufiene, B. O., Jamjoom, M. M. and Ullah, Z. (2022). MobiRes-Net: A Hybrid Deep Learning Model for Detecting and Classifying Olive Leaf Diseases, *Appl. Sci., 12*, 10278.
85. Anitha, J., Saranya, N. (2022). Cassava Leaf Disease Identification and Detection Using Deep Learning Approach, *International Journal of Computers, Communications and Control, Oradea 17(2)*.