

Study of digital image processing techniques for leaf disease detection and classification

Gittaly Dhingra¹  · Vinay Kumar¹ · Hem Dutt Joshi¹

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Abstract In this paper, we address a comprehensive study on disease recognition and classification of plant leafs using image processing methods. The traditional manual visual quality inspection cannot be defined systematically as this method is unpredictable and inconsistent. Moreover, it involves a remarkable amount of expertise in the field of plant disease diagnostics (phytopathology) in addition to the disproportionate processing times. Hence, image processing has been applied for the recognition of plant diseases. The paper has been divided into two main categories viz. detection and classification of leafs. A comprehensive discussion on the diseases detection and classification performance is presented based on analysis of previously proposed state of art techniques particularly from 1997 to 2016. Finally, discussed and classify the challenges and some prospects for future improvements in this space.

Keywords Computer vision · Image analysis · Plant leaf diseases · Feature extraction · Segmentation · Classifiers

1 Introduction

Plants and fruits are the primary source of energy for the human as well as animals. Leafs of various plants and herbs are useful to mankind due to their medicinal attributes. Countries like Asia and Africa where over 50% of population depends on agriculture production for

✉ Gittaly Dhingra
gittaly@thapar.edu

Vinay Kumar
vinay.kumar@thapar.edu

Hem Dutt Joshi
hemdutt.joshi@thapar.edu

¹ Electronics and Communication Engineering Department, Thapar University Patiala, Patiala 147001, India

employment, export earnings and food security [79]. It is assessed that 30 to 40% of crops are lost each year through the production chain [26]. Losses from diseases also have an important economic impact, causing a drop in income for crop producers, higher amounts for consumers and distributors. A lot of studies have been carried out under changed environmental conditions, in different locations, to estimate the losses occur due to different diseases.

In 1980, it was assessed that the annual loss due to plant diseases in U.S.A was about four billion dollars while in India it was probably even more than that [65]. Pre and post-harvest fungal diseases crop losses annually exceed \$200 billion euros and over \$600 million are annually spent on fungicides [28] in the United States alone. In 2007, the loss within the jurisdiction of Georgia was about \$539.74 million, where about \$185 million was expensed to control the diseases, and the rest was use to pacify the damage caused by the diseases. So plant disease resistance and managing are crucial to the consistent production of food [13, 49]. Less than 25% of Malawi farmers attained self-sufficiency in maize in years (2000–2001) [21]. According to the study in the Georgia it is estimated that in the year 2010, approximately \$701.2 million plants diseases losses considered including control costs. The cost of crops estimate was approximately \$4236.51 million, resultant in a 16.5 total percent disease loss across all crops included. In India, the annual estimated losses due to nematodes have been assessed out to be about Rs. 242.1 billion.

The above mentioned illustrations validate that various parts of the world where a large proportion of the population is reliant on a single or a few crops, is at risk, since a crop failure due to devastating disease can lead them to starvation [47]. Thus there is a need to evaluate the quality of plant so as to identify any disease in them that can be a potential danger to the life of the plant, thereby contributing towards economical, biological, sociological and ecological losses. Plant diseases can be broadly classified either infectious or noninfectious. The demand for high level of safety and superior quality in agricultural products is of prime concern. The foundation of quality assessment is basically dependent upon features of leafs such as its

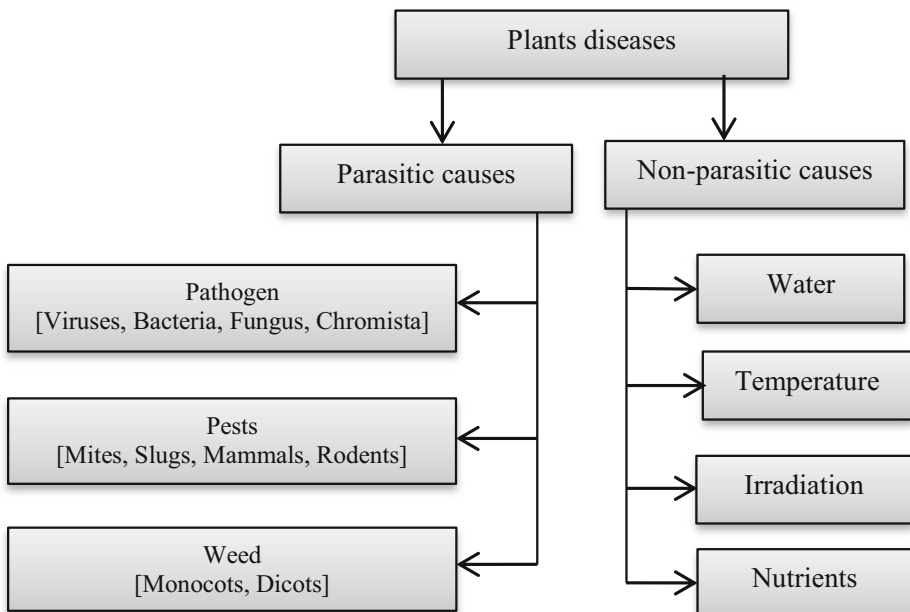


Fig. 1 General structure of types of plant diseases

appearance, cracks, texture, and surface where human alertness could be easily fooled. Figure 1 demonstrates the general structure of categorization of plants diseases.

The demand for high level of safety and superior quality in agricultural products is of prime concern. The different methods such as thermography [19, 47], immunofluorescence techniques [83], fluorescence imaging [44], gas chromatography techniques [24], chain reactions [17] and DNA/RNA based affinity biosensor [23] etc. have been often used for quality evaluation of leaves. The problem of the above mentioned techniques were inefficiency, inconsistency and broadly prolonged. Therefore, consideration for an automatic and precise along with inexpensive and efficient technique to identify plant disease is of great realistic significance.

By now, studies show that the image processing methods work as effective tools for the identification and classification of plants diseases. Major advances have been made to improve reliability, precision and accuracy of image analysis for detecting and classifying plant diseases over the last 25 years. It is stated that more than 1000 papers are published each year in the growing fields of computer vision and image processing. The important doctrine and standards remain the same but calculations and testing became more accurate with the application of computer vision technology. The image analysis technique is used to distinguish the objects from the background, thereby isolate quantifiable information which is used in various control systems of decision making. In fact, about 60% to 70% of disease appears on leaf only. So, we have interest in the plant leaf rather than whole plant. This paper represents the latest growths and improvements of the computer and image processing methods in the strata of plant leaf diseases detection, identification with an emphasis on image processing in a significant way.

2 Leaf diseases and symptoms

The quality of leaves defines the degree of excellence or a state of being free from defects, deficits, and substantial variations. It depends on many factors such as sowing seeds, temperature, transplanting, and harvesting etc. [25, 31]. Plant leaf diseases can be mostly categorized based on their nature of their key causal agent (i.e. infectious and noninfectious). Infectious leaf diseases are instigated by a pathogenic organism such as a bacterium, mycoplasma, fungus, virus, nematode, viroid etc. An infectious agent is proficient of reproducing within or on its host and scattering from one susceptible host to another host. On the other hand, noninfectious plant diseases owe their origin to critical growing conditions, disadvantageous relationships between moisture and oxygen, excesses of temperature, toxic constituents in the soil or atmosphere, and deficiency of an essential mineral. Noninfectious causal agents are not contagious and not proficient of reproducing within a host. Table 1 briefly represents the mostly occurring leaf disease and their symptoms and descriptions [16, 75].

3 Challenges of image processing

Computer vision technology has been studied and broadly used in agriculture applications to recognize and classify plants leaf diseases. In the presented study we emphasize on latest studies that reflect image processing methods contribution in the detection of plants leaf diseases and their classification under various field conditions. Figure 2 represents a methodology structure for detection of diseases and their classification techniques. This survey is structured as follows: Section 4, describes an assessment of classification and identification

Table 1 Leafs disease symptoms

Plants leafs disease symptoms	Descriptions	Plant pathogen group
Blotch	Large spot on leaf	Water molds, viruses and phytoplasmas
Bronzing	Develop a bronze color	Water molds, viruses
Blight	Discoloration, wilting	Viruses, nematodes and phytoplasmas
Chlorosis	Yellowing	Phytoplasmas
Leafs pot	Lesion on a leaf	Nematodes and phytoplasmas
Fusarium wilt	Dropping of leaf	Fungus
Distortion	Irregular shaped leaf	Nematodes
Gall	Abnormal and swelling on leaf	Water mold and viruses
Mosaic	Non-uniform foliage coloration	Fungi, bacteria and nematodes
Ring spot	A lesion with a dark outer ring	Fungi, water molds and nematodes
Rugose	Wrinkled surface of leaf	Bacteria
Scrab	Lesion like crust	Viruses and nematodes
Scroach	Browning	Viruses
Vein clearing	Leaf veins becomes yellow	Fungi and bacteria
Water soaking	Wet, dark or greasy lesions	Viruses
Downy mildew	Yellow and brown color lesion, fuzzy growth	Fungus
Gray mold	Lesion, leafs drying	Fungus
Flea beetle	Small holes or pits	Insect
Slugs & snails	Irregular shaped holes in leaf	Molluse
Cercospora leaf spot	Circular to irregular dark spots on leaf with light center	Fungus
Aphids	Small soft bodied insects on underside of leaf, yellow color, pink and brown color	Insect
Shot-hole	Lesions where centers have fallen out	Viruses and water mold

approaches, a comparison of segmentation technique based on recent studies. Section 5, briefly discuss an overall remaining challenges, limitations, and discussion. Section 6, explains the conclusion and future scope of mentioned techniques in literature.

4 Literature review

Pathologists focus on diseases in different parts of the plant like roots, kernel, stem and leaf. As discussed earlier, the present paper concentrates, particularly on leafs. A large amount of the information on the identification of disease and classification field can be found in the various papers [11, 27, 40, 69]. It usually includes preprocessing stage, selection of segmentation techniques followed by the identification and classification stage using selection of proper techniques. The work is divided into two subsections. The first sub-section emphasizes on the contribution of researchers with respect to the technical explanations considered in their algorithm and a summarizing table which contains the information regarding technical culture. In the subsequent sub-sections, a concluding segment is presented with remarks on the contribution of researchers. Certain features common in mostly used methods are offered in this section: the images are acquired via consumer level cameras in a suitable laboratory situation, and the format used for the images are RGB, CIELAB etc. All the methods apply some kind of preprocessing to avoid the noise, segmentation process to select the region of interest (disease) and so on. Figure 3 represents the basic set up of leaf diseases detection and their classification. Therefore, unless

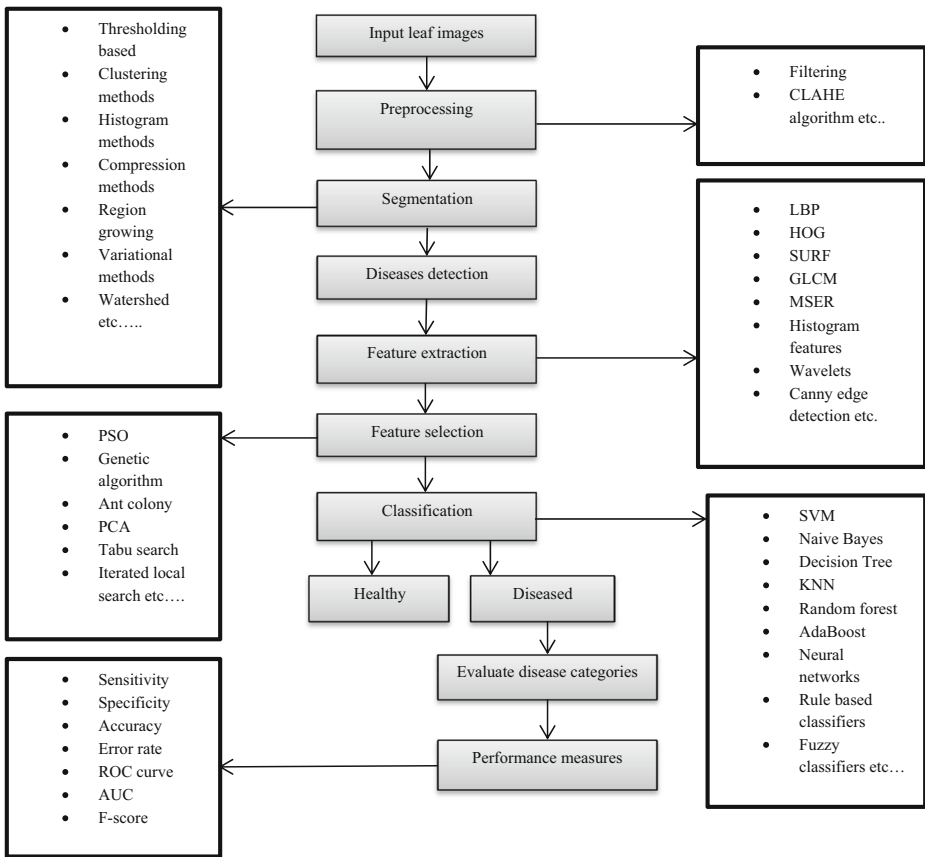


Fig. 2 General Structure for diseases identification and classification of plant leaves

stated otherwise, these are the situations under which the described methods operate. Also, practically all the methods mentioned in this paper apply some kind of preprocessing to clean up the images but we are not focusing much on these techniques.

4.1 Disease detection analysis with color and texture characteristics

This section represents the review of various techniques used for the identification of diseases using texture and color characteristics.

Pydipati et al. [63] represents the color co-occurrence method (CCM) to determine texture based hue, saturation and intensity (HSI) color features in the combination with statistical classification algorithms to classify diseased and normal citrus leaves. In the first stage, features are extracted using CCM by considering the four different categories of leaves. Further, SAS statistical analysis is used to evaluate the potential classification accuracies with reducing the variable sets and using color features individually. However, best results were attained using combined HIS features. The authors explicated that hue and saturation features are influenced by low lighting conditions and such methods prove to be the best under controlled laboratory lightning conditions. The most significant challenge is to used this method under natural lightning conditions.

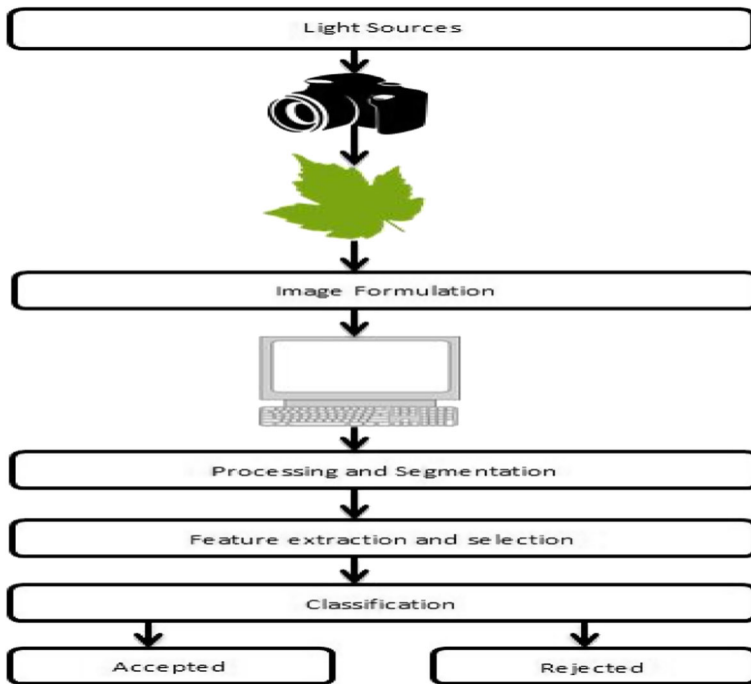


Fig. 3 Basic set up of leaf diseases detection and classification model

A. Camargo et al. [18] presented image processing method to identify the plant diseases visual symptoms from the exploration of colored images. They transformed an RGB color space of the diseased leaf into H, I3a and I3b transformation. The I3a and I3b conversions are generally developed from an adjustment of the original I1 I2 I3 color transformations to meet the requirements. By analyzing the scattering of the intensities in a histogram, transformed images are segmented. After post processing, it checked the accuracy by manually comparing the segmented images of plant leaves with automatically segmented images. The authors concluded that this technique is suitable to identify a diseased segment even when the segment is represented by an extensive range of various intensities.

Haiguang Wang et al. [82] described a method for the identification of diseases in grape and wheat leaves. Firstly, captured images were transformed from RGB color space to XYZ color space and then again transformed from XYZ color space to L^*a^*b color spaces. Squared Euclidean distance (D) as a similarity distance is used to evaluate the color difference in a^*b , a two dimensional data space. Total 4 shape features, 21 color features and 25 texture features are extracted to distinguish various diseases. Furthermore, for reducing dimensions in the featured data processing, Principal component analysis (PCA) is performed. Later on, different neural network techniques with different parameters including Back Propagation (BP) networks, Generalized Regression Networks (GRNNs) and Probabilistic Neural Networks (PNNs), Radial Basis Function (RBF), were used to classify and identify wheat and grape leaf diseases respectively. The author confirmed that this technique provides a fast and precise recognition of plant diseases. Table 2 describes the various color space advantages and disadvantages.

Table 2 Comparison of various segmentation techniques

Color space	Classification	Advantages	Disadvantages
RGB	Device dependent	Appropriate for display.	High correlation between channels.
HIS	User oriented device dependent	Suitable in variation illuminations level, because hue (H) is invariant (i.e. shadows, shading etc.).	Unstable at low saturation level.
I1,I2,I3	Device dependent	Involves less computation time.	Due to correlation between channels, not good for color image processing.
YUV	Device dependent	Fast and efficiently encode color information in the TV signal of European system.	Due to linear transformation, correlation still exists.
CIE spaces	Device independent	Perceptually uniform	Have the same singularity problem as other nonlinear transformations.
YIQ	Device dependent	Efficiently encode color information in the TV signal of American system.	Due to linear transformation, correlation still exists.

Qinghai He et al. [32] proposed the diseases identification method for cotton leaf in which three color models are used for extracting the disease. Firstly, images are captured and to eliminate the influence of noise, spatial non-linear and frequency domain filtering is used. Afterwards, the edges of background image are highlighted by using histogram equalization process and then the contrast of the image is raised. The enhanced images are converted into the RGB, HIS, and YCbCr color model. The percentage of damage (γ) is selected as a feature to evaluate the amount of damage due to leaf diseases or pests. After applying different color models, comparative results were obtained. The comparison of the results show YCbCr color format measured as the best color model for identifying the injured color leaf image. The author validated that the projected algorithm fails to handle the random noise interference and leaf shadow in case of outdoor conditions.

Auzi Asfarian et al. [8] presented the work on paddy diseases identification using the fractal descriptors based on Fourier transforms with texture analysis. Here, injuries (lesions) are collected manually and then each of these lesion images were transformed to HSV color space. Histogram equalization is performed for reducing the lightning effects after extracting the saturation components. Conclusively, from each lesion, the fractal descriptors were extracted and then given to PNN classifier for concluding the classification. 5-fold cross validation used to split the training and testing data for verification and validation. The author stated that this method, if it is combined with other features has a prospective to be used as one of the possible features, especially when two diseases comparatively involved have the same color.

Pradnya Ravindra Narvekar et al. [58] discussed the effective way of disease detection in grape leaves using SGDM (spatial gray level dependence matrices) method. They used four classes of leaves under different disease conditions (i.e. Black rot, downy mildew, powdery mildew and normal). After color transformation of RGB to HSI, the H component is considered for further analysis. The S and I components were throw down since they do not provide any useful information. Based on the specified and varying threshold, green pixels were masked using Otsu method. In the next step the pixels with zero red, green and blue color values were entirely removed. Later on, features based on the color and texture were extracted and classified in different disease category. The authors concluded that the proposed work indicates the valuable approach with little computational efforts but with the use of hybrid algorithms, the recognition rate of classification can be increased.

Vinita Tajane et al. [78] suggested CBIR (content base image retrieval) method for identifying medical plants leaf diseases using canny edge detection algorithm and histogram analysis. In the first stage, CBIR smooth the image to eliminate the noise and finds the image gradient to highlight regions with high spatial derivatives. In the next stage medical plant leaf diseases were detected based on its edge features. Firstly, leaf images are transformed into gray scale images and edge histogram is calculated. The area and color features of the image are evaluated using histogram for the overall image. Based on their research, they evaluate color histogram for each red, green and blue color region individually to check the intensity of each color pixels in the sample image for identification of healthy and infected sample. The author concluded that Canny edge detection algorithm is an effective method for distinguishing edges of healthy and infected plants and it also filters useless information and preserve significant structural properties in an image.

Juan F. Molina et al. [54] presented a color based strategy to detect an early blight disease or any kind of infection on tomato leaf lets. The proposed method based on the categorization of tomato leafs with the help of color descriptors. Color characterization is done using color structure descriptors (i.e. color histogram by quantifies the amount of significant color) using Hue-Max-Min method, scalable color descriptor (i.e. leading spatial color distribution) and color layout descriptors (color pattern variation) using YCbCr color space transform. After calculation of all these feature or descriptor values, a novel strategy based on nested leaf one out cross validation method is used to achieve better classification ratio. The individual descriptor configuration evaluation performed using an inner loop permit, while the outer loop measures performance assessment between different descriptors. The author concluded that color structure descriptor provided better accuracy than other methods. Table 3 represents the summarization of color and texture technique for diseases detection.

4.2 Disease detection analysis with thresholding and clustering parameters

This section characterizes the review of various techniques used for diseases identification using thresholding and clustering parameters.

Tucker and Chakraborty [81] focused on identifying and detecting diseases in oat and sunflower leaves. Firstly images were segmented with varying threshold w.r.t the disease being measured (blight or rust). Then, using clustering, subsequent pixels were connected into clusters for signifying the diseased regions. Based on the features of the lesions, they are segregated into the proper categories. The authors observed good results but due to inappropriate illumination during the capturing of the images, some errors exist.

D.G. Sena Jr. et al. [73] proposed work to develop a procedure for identifying damaged maize plant leaf diseases at simplified lightning conditions. Damaged and healthy maize plant leaf images were captured in three different light intensities and in eight different locations. The proposed algorithm is divided into two stages: preprocessing and the image analysis. During the first stage the original RGB images were transformed to 256 grey level images by applying the additional green index and rescaling the pixel values to create binary images. Then, the monochrome images were threshold by the iterative method. In the second stage, the images were sectioned into blocks and classified as healthy or damaged based on the number of objects originated in each block. The author concluded that the proposed algorithm perform well and gives good accuracy.

Shen Weizheng et al. [84] have implemented an image processing based technique for analyzing the leaf spot disease. They investigated all the influencing issues that existed in the

Table 3 Summarization of color and texture technique for diseases detection

Proposal	Culture	Diseases	No. of images considered	Accuracy	Features	Image format	Environment conditions	Image acquisition device/standard dataset
R. Pydipati et al. [63]	Citrus leaf	Melanose, greasy spot & scab	Total 40 images 20images[training] 20images[testing]	96%	Intensity texture features	Uncompressed Jpeg format	Controlled lighting conditions	3 CCD camera (JAI, MV90) captured from central Florida
A.Camargo et al. [18]	Banana, com. soya, alfalfa	Fungal	Total images not defined 20 images[testing]	N/A	Histogram Based different intensity distribution	Jpeg format	N/A	Images collected from Department of Entomology, at the University of IOWA, USA supplied the images of maize and alfalfa. The Department of Entomology, University of Georgia, supplied images of cotton and soya. The International Network for Improvement of Banana and Plantain field
Haignag Wang et al. [82]	Grapes & wheat leaf	Rust, downy & powdery mildew	Total 185 images 110[training] 75 [testing]	94.29%	Color, shape & texture feature	Jpeg format	Controlled lighting conditions	Common digital camera
Qinghai He et al. [32]	Cotton	Fungal & bacterial	N/A	YCbCr more accurate	Ratio of damage	N/A	Controlled lighting conditions	Common digital camera
Auzi Asfarian et al. [8]	Paddy crop leaf	Leaf blast, brown spot, bacterial leaf blight & tungro	Total 40 images 5 fold cross validation	83%	Fourier descriptor	N/A	N/A	Images were taken in paddy field in Laladon and Cipanas, West Java, Indonesia using common digital camera
Pradnya Ravindra Narvekar et al. [58]	Grapes leaf	Black rot, powdery, downy mildew	100 images	N/A	Color & texture features	N/A	N/A	N/A
Vinita Tajane et al. [78]	Medicinal plants leaf	Fungal, virus & bacterial	N/A	N/A	Color Histogram features	N/A	Controlled lighting conditions	Common digital camera
Juan F. Molina et al. [54]	Tomato leaf	Early blight	190 ROI images	100% [CSD64]	Colors descriptor	Jpeg format	Controlled lighting conditions	Captured at tomato green- house crop Boyaca Region, Colombia

process of segmentation. Leaf regions were segmented using Otsu thresholding. After color transformation from RGB color system to the HSI color system, H element is selected for segmentation of the leaf spot to reduce the disruption of lightning changes. Further, Sobel operator is considered in order of observing the edges of the leaf disease spots. Finally, grading is achieved by assessing the quotient of the diseased region and leaf areas. The author indicates that this method, to grade plant leaf spot diseases is fast and accurate.

Kurniawati et al. [45] defined a technique to detect and label three different kinds of diseases namely brown spot blast and narrow brown spot that influence paddy crops. The healthy and diseased region segmentation is accomplished by means of thresholding using Otsu's and local entropy. Color, texture and shape features are extracted to decide the diseases that best fits the characteristics of the selected region. The characteristics of image consisting of boundary color, spot color, lesion type and broken paddy leaf color from paddy leaf images. The best accuracy achieved is by using local entropy threshold. The final classification is done by discriminating between the selected regions according to the corresponding predefined set of rules. The author concluded that the Otsu thresholding method is unable to accomplish segmentation task correctly to different intensity standards and less susceptible to illumination.

Sekulska-Nalewajko and Goclawski et al. [72] presented a method to detect disease signs in cucumber and pumpkin leaves. Firstly after capturing, the images were converted from RGB to HSV color space format. After thresholding the leaf area, the brightness section is discarded. Then, Fuzzy c means clustering algorithm is applied in hue-saturation space in order to group the pixels into clusters. These clusters are then combined with the interactive phase into two final clusters, where one of them decides the searched disease areas ultimately, the author justified that the present approach gives good classification results. However, this approach requires too many processes to achieve the desired results.

Zulkifli Bin Husin et al. [35] discuss the effective method used for evaluating primary detection of chili disease using leaf features inspection. Now days, from time to time the chemicals are applied to the plants without seeing the prerequisite of each plant life cycle. This technique will confirm that the chemicals are applied only when the plants are noticed to be instigated with the diseases. Firstly, leaf images are captured under controlled field condition and preprocessing is done to achieve improved image information. Features are extracted using color information for differentiating between healthy and non-healthy leaves. The resultant color pixels were gathered to achieve different groups of colors in the image to distinguish the disease affected area of leaf. In the end, histogram graphs are evaluated to measure the healthiness of leaves. The author concluded that the proposed method is fast and efficient in recognition of plant chili disease.

Revathi et al. [67] defined two segments to categorize the affected part of the leaf using proposed homogeneous pixel counting technique for cotton diseases detection (HPCDD) technique. Initially, sobel edge detection method is used to recognize the diseased segments of the leaf spot and distinguish the diseased boundary. Then evaluate the entered pixels of opposed neighboring one, two, three pixels of clarity of edges. The Homogeneity based edge detector precedes the result of any edge detector and splits it by the average range of the part. The average range of an area is calculated by convolving the part with a mask containing all the ones. Finally, extracted edge features are used in the classification process to classify the disease spots. The author testified that the proposed method provides good accuracy than other existing algorithms.

Mokhled S. Al-Tarawneh et al. [5] suggested a method to detect diseases in olive leaves. The proposed method combines auto cropping technique with fuzzy c means clustering to identify

the disease. After, color transformation of RGB to CIELab color space, the region of interest (diseased region) is cropped using automatic polygon to segment the leaf. The polygon cropping follows the edging contour of entire image to define the masked polygon points of diseased segments. At the end, classification is done using fuzzy c-means clustering for statistical usage to define the defect and severity. The severity percentage is calculated based on the classification of detected diseased and total leaf area. The author actualized that the experimental results of FCM algorithm with polygon auto-cropping segmentation shows encouraging accuracy prospects. Table 4 represents the various advantages and disadvantages of the segmentation techniques.

D. Zhihua et al. [92] discussed cotton mite diseases recognition approach using color features and thresholding methods. Proposed technique is distributed into three steps: 1) diseases spots and stems extraction of the green plants. 2) Special features detection in gray histogram and transform the segmented image into 8-bit gray scale image using thresholding. Histograms illustrated two points in two different gray scale portions as disease spotted portions with values 255 and grayscale values less than 120 depicted as non-disease spotted portions. The black pixels signified the corresponding disease spotted part taking mite disease spots, stems and white pixels representing non-disease spotted areas. 3) Segmentation of binary images using area thresholding and comparing the areas with spots to the stems. The author concluded that the mite and stem disease spotted portions are almost similar in color therefore it is a difficult task to compare the areas with spots on the stems.

Krishnan et al. [42] defined approach to analyze shade leaf's disease (i.e. bacterial scotch). Firstly, shade tree leaf's images were attained under controlled lightning conditions, followed by clustering based approach. K-means clustering approaches utilize distinct clusters and accomplish different cluster centers to achieve different clusters for defining region of interest. Final clustering is achieved by subtracting reference images from base images to form convoluted clusters from original images. The authors concluded that the proposed algorithm gives high accuracy with less operational time. But, the classification of algorithm can be improved by updating the clusters through repetition procedure. The clustering algorithms built on limitations and certain relaxation algorithms could also be improved to provide accuracy to the proposed scheme.

Eric Hitiman et al. [33] explained a technique for leaf injury detection and severity assessment of coffee leaf. Further, Gaussian kernel is used to suppress the noise and image

Table 4 Comparison of various segmentation techniques

Segmentation Techniques	Advantages	Disadvantages
Region based segmentation	More noise immune, Works well in homogenous regions	Computationally complex, Slow
Watershed segmentation	Computationally efficient	Over segmentation
Edge based approaches	Works well for images having good contrast.	Less immune to noise, Inaccurate sometimes, Complex computation
K means segmentation	Tighter clusters than hierarchical methods, particularly if the clusters are globular, faster	Prediction of K-value is difficult.
Histogram thresholding	Less computational complex, Do not need prior knowledge	Does not consider the spatial details.
Neural networks approaches	Less complex, Fast	Training time is long, Overtraining avoided

color space is transformed into CIELAB color space. After increasing the contrast image with Look up Table (LUT) based gamma correction using average pixel intensity. Later, the boundary features of the threshold image are detected using canny edge detector and joined to modify the overall structure of the object. Using background removal method based on luminance and color, only leaf area (foreground) is extracted and the background free leaf image is processed with YUV color space (i.e. V channel) to maximize leaf injury detection. Finally, leaf damage severity is assessed w.r.t to percentage of pixel distribution of the damaged and healthy leaf. The author consummated that the proposed method is fast and avoids the defoliation. Moreover, the proposed method can handle all the images (i.e. destroyed and color changes) and provides good accuracy rate. Table 5 represents the summarization of thresholding and clustering techniques for diseases detection.

Jiangsheng Gui et al. [29] proposed a novel method for the identification of diseases of soybean leaf by means of salient regions using color image with complex background. Based on idea of Itti method and low level features of luminance and color, salient regions are detected. Then w.r.t combined experience threshold and K-means algorithm salient regions can be precisely extracted from the images of diseased soybean leafs based on salient maps. In the last, segmentation using threshold is performed on R component of RGB space. Morphology algorithm is used to fill small holes and eliminate the insignificant small sized regions of the non-diseased area to correct the diseased segment. The author finally conferred that the proposed technique using salient regions can rapidly and precisely detect the segment of diseases in complicated farmland backgrounds.

K. W. V Sanjaya et al. [70] proposed system to measure and predict orchid leaf healthiness and diseases. Gaussian operator and histogram equalization method is used for removing noise and enhancing the image. After, enhancing the image, we acquire the orchid leaf object by removing the background noise in the image. Next, we input RGB image and it is transformed into the HSV color model and apply thresholds for hue, saturation and value color bands separately. Threshold values are manually selected by observing the histograms of three color bands for segmenting the green and yellow objects. After segmentation, image shape and color features are extracted to detect orchid leaf diseases. The extracted geometric features of the leaf image are used to predict the orchid species and the color features are used to predict the healthiness of the orchid plant. In order to make predictions, decision trees method is used. The author concluded that proposed system accuracy is reliable but the system can identify only three orchid species and three orchid diseases.

Sourabh Shrivastva et al. [74] presented a technique to automatically identify and estimate the level of disease severity in soybean plant foliar. The concerned method converts the RGB image into the Y , C_b , C_r channels and then segments through simple thresholding method. The authors used various novel parameters such as disease level parameter, severity index, diseases severity index and infected area to automatically measure the disease level severity. The author highlighted that it is a low cost method and has the potential for the extensive usability in field conditions. Moreover, the performance of this method might be improved by using unconventional background separation approach to distinct the leaf object from a complex background.

Amar Kumar Dey et al. [76] considered image processing procedures to identify leaf rot disease by classifying the color feature of the rotted leaf region of betel vine. After analyzing different color spaces, HVS gives promising results where the hue component provides the strong remark of rotted leaf area. Afterwards, using Otsu thresholding method rotted area is segmented using various threshold values and area of rotted portion is considered as the feature

Table 5 Summarization of thresholding and clustering techniques for diseases detection

Proposal	Culture	Diseases	No. of images considered	Accuracy	Features	Image format	Environment conditions	Image acquisition device/standard dataset
Tucker and Chakraborty et al. [81]	Sunflower & oat leaf	Rust & blight	Upto 20 for each disease	N/A	Area, size & diameter	N/A	Controlled lighting condition	TMC-76 color CCD
D.G. Sena Jr. et al. [73]	Maize leaf	Fall armyworm	720 images	94-72%	N/A	N/A	Controlled different lighting conditions	Digital camera, MS3100, captured from greenhouse at Embrapa Com & Sorghum, Sete Lagoas, MG, Brazil
Shen Weizheng et al. [84]	Soybean	Leaf spot	N/A	N/A	Diseased spot & area	N/A	Controlled lighting conditions	Common digital camera
Sekulska-Nalewajko et al. [72]	Pumpkin & cucumber	Bacterial	N/A	N/A	N/A	Jpeg format	Controlled lighting conditions	Scanner
Kumiawati et al. [45]	Paddy crop	Blast, brown narrow & brown spot	94 images	94.7%	Color & shape	BMP format	N/A	Canon PowerShot G2 digital camera
Zulkifli Bin Husin et al. [35]	Chili leaf	Fungal & bacterial	107 images	N/A	Color	Jpeg format	Controlled lighting conditions	Common digital camera
P. Revathi et al. [67]	Cotton leaf	Leaf spots	N/A	98.1%	Color	Jpeg format	Images captured in field	Digital mobile camera
Mokhled S. Al-Tarawneh et al. [5]	Olive leaf	Leaf spots	100 images	86%[FCM] 66%[KMC]	Color segment	Jpeg format	Uncontrolled lighting conditions and captured in field	N/A
D. Zhihua et al. [92]	Cotton leaf	Mite diseases	30 images	94.79%	Diseases spot area	Jpeg format	Controlled lighting conditions	Nikon D90 SLR digital camera
Krishnan et al. [42]	Shade tree	Bacterial	N/A	N/A	Area	Jpeg PNG	N/A	N/A

Table 5 (continued)

Proposal	Culture	Diseases	No. of images considered	Accuracy	Features	Image format	Environment conditions	Image acquisition device/standard dataset
Eric Hitman et al. [33]	Coffee leaf	Bacterial	Training data not defined 27 images [testing]	N/A	Area	N/A	Controlled lighting conditions	Common digital camera
Jiangsheng Gui et al. [29]	Soybean leaf	Fungal & bacterial	N/A	N/A	Salient region	N/A	Controlled lighting conditions	Images are taken from Hefei academy
K. W. V Sanjaya et al. [70]	Orchid leaf	Phyllosticta, yellowing & black rot	250 image set	84% [segmentation] 80.7365% [J48] 79.0368% [Naives Bayes] 91% [orchid specie]	Color & geometric	N/A	Uncontrolled lighting conditions	Smart phone camera
Sourabh Shrivastva et al. [74]	Soybean leaf	Frog eye, rust bacterial blight, downy mildew & sudden death syndrome	1000 images	N/A	Color & area	Jpeg	Images captured in field	Mobile phone Samsung GT-S3770 agricultural field in Guna district of Madhya Pradesh, India.
Amar Kumar Dey et al. [76]	Betel vine	Rotten	12 images	N/A	Color	Jpeg	Images captured in field	CanoScanLiDE 110 [Scanner] Dhara, Rajnandgaon district of Chhattisgarh

set. A leaf disease severity scale can be prepared by calculating the proportion of diseased area. Using frequency of precise amounts of pesticide application, disease severity volume can be regulated, which moderates the pesticide cost used for management. The author concluded that the results presented promising results of this automatic vision based system with easy validation.

4.3 Diseases classification using artificial neural networks

This section describes the review of various techniques used for classification of diseases using Artificial Neural Networks (ANN).

Kuo-YI Huang et al. [34] explained an approach using artificial neural networks for recognition of *Phalaenopsis* seedling diseases with texture and color analysis. Lesion areas were segmented using underlining principle to differentiate background (pot), object (leaves) and exponentially transform a variable parameter to enhance the image and to evaluate texture features of the lesion area Gray Level Co-occurrence matrix (GLCM) used. After that, tri-color mean values of lesion areas are employed to classify diseases. The back propagation neural network classifier is then used to categorize various defects. Finally, authors were able to distinguish and categorize visible lesion areas but they were incapable to examine the infected area on the enclosed blades. The recognition and classification system can be also useful for the development of flowers and plant leaves in greenhouse.

Noor Ezan Abdullah et al. [1] classified the diseases in rubber tree leaves using multilayer perception neural networks. After the preprocessing by using median filter, the color features were extracted using RGB distribution indices to calculate the region of interest (i.e. lesion spots). The Principal Component Analysis (PCA) is employed on the progression values of each image. The improved artificial neural networks designed were based on optimized dominant pixel (mean) of RGB and normalized PCA data. The optimized models were then evaluated and validated through analysis of various performance indexes. According to authors, the proposed method is found to be the best models for identify bird eye spot and orichum diseases. However, the effectiveness of this classification can be increased providing a better processor and high resolution camera is employed.

Santanu Phadikar et al. [60] defined the framework to identify the diseases of rice plant leaves using zooming algorithm and neural networks. The input RGB color space images are converted into HIS color space images and the infected regions are extracted using entropy based thresholding method. Then, the features are extracted using zooming algorithm and are classified using Self Organizing Map (SOM) neural network where train images are obtained by extracting features of the infected parts of the leaf while four different types of images are applied for testing purposes. The authors explained that it is a simple and computationally efficient technique, which results in a satisfactory classification of results. However, it has been observed that the transformation of the image in the frequency domain does not produce a better classification parallel to the original image.

Dheeb Al Bashish et al. [12] suggested a structure for classification and identification of diseases such as early scorch, ashen mold, cottony mold, late scorch and tiny whiteness etc. Subsequently color transformations of RGB into HIS color space, the images are clustered with K-means clustering approach using Squared Euclidean distance. This method segregates the leaf image into four clusters and evaluates the color and texture features, SGDM matrices are created for each pixel map of the image but only for H and S component. Statistical examination tasks are accomplished to select the best features for reducing the feature

redundancy. Then for final classification, neural network classifier is used. It is found that the proposed method can expressively support precise and automatic recognition of diseases in leaves. However, due to invariability in lighting conditions some samples of diseased leaves were misclassified. An example of the output of K-Means clustering for a leaf infected with early scorch disease is shown in Fig. 4.

H. Al. Hiary et al. [4] shed light on an automatic disease detection method based on K-means segmentation process. In the proposed method, the pixels were categorized to K number of classes on the basis of a set of features, which masked the green pixel values obtained using the Otsu's thresholding technique. Features are extracted using color co-occurrence matrix to analyse affected leaves texture. The leaf spots are considered as an indicator of crop diseases. In the end, the classification of diseases is evaluated using artificial neural networks. The author concluded that this method requires small computation of time and computational effectiveness.

Wanrat Abdullakassim et al. [2] elucidated an image analysis method for recognition of brown leaf spot disease. Various color descriptors or color indices i.e. RGB and HIS descriptors were used to recognize different regions of leaf based on its color. The range of color indices of RGB and HSI varies from 0 to 1. Then, ANN is used to classify or differentiate between an infected region and a healthy region. Brier score is employed to estimate the recognition capability of the ANN with more hidden layers. It is found that this algorithm properly identifies 79.23% diseased leaves and 89.92% healthy leaves, but this study also includes misclassification of infected leaves. This method can be improved by combining the lightning conditions, effects of infection phases and proper segmentation.

Kai et al. [39] suggested a technique to recognize diseases in maize leaves based on neural networks. Firstly, the images were transformed to the YCbCr color illustration to evaluate Cb and Cr components because they are less affected by brightness. In this two dimensional plane, the lesion area is relatively concentrated in accordance with Gaussian distribution. After that

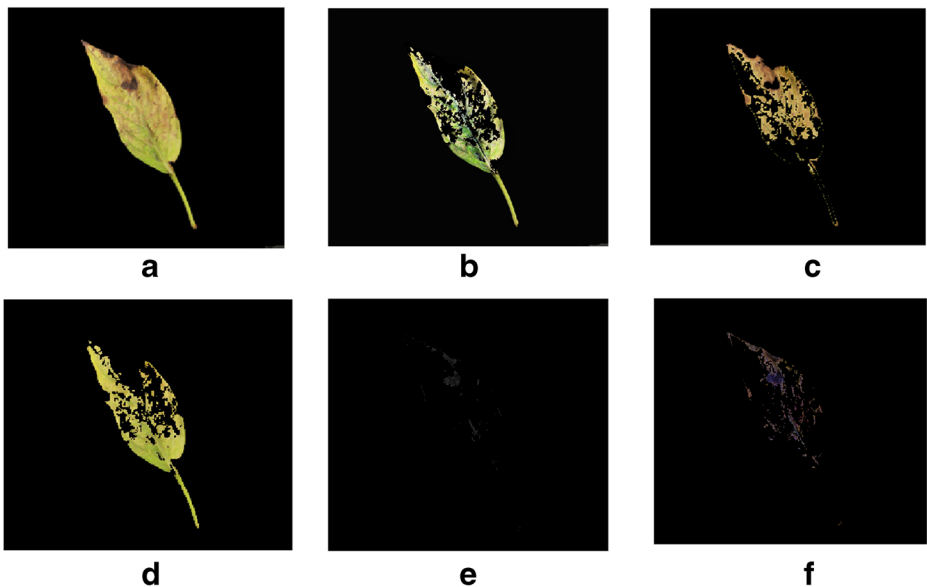


Fig. 4 An example of the output of K-Means clustering for a leaf that is infected with early scorch disease (a) The infected leaf picture. (b, c, d, e) the pixels of the first, second, third and fourth cluster, respectively

texture features are evaluated using SGLCM matrix. Furthermore, the back propagation based neural networks with sigmoid function using 3 hidden layers are used to classify various diseases. The exploratory results proclaimed that the accuracy is very high. The author concluded that a neural network error value is very low, weight design is reasonably correct and overall performance is good.

D.S. Guru et al. [30] discussed innovative idea for extracting lesion areas from tobacco leaf using neural networks. Contrast stretching transformation with an adjustable parameter and morphological operations are used to segment lesion areas. R channel based statistical texture features (i.e. statistical moments, uniformity and entropy) are extracted from lesion area to identify and analyze the diseased category. Based on extracted texture features, Probabilistic Neural Network (PNN) is used to categorize tobacco seedling leaf diseases as anthracnose and frog-eye spots. The author concluded that the first order statistical texture features perform better than Gray level co-occurrence matrix features. Classification accuracy can be improved with combination of different color and texture features.

Tushar H Jaware et al. [37] explained an effective and precise method for classification and recognition of leaf diseases. The suggested procedure is validated on five diseases; early scorch, cottony mold, late scorch, ashen mold and tiny whiteness. Primarily after the color transformation, pattern of input RGB color space to HIS format, K-means clustering technique is used for segment diseased region. Furthermore the red, green and blue zero pixel values and boundary pixels of the diseased leafs were completely removed and masked the green pixels only. Next, the diseased clusters were transformed back from HIS format to RGB format and SGDM matrices were generated for each pixel map of the image and extracted the features for further classification. Lastly, the features were trained using a pre-trained neural network. The results showed that the suggested system can be effectively distinguished and the diseases are categorized.

Weidan Zhang et al. [90] proposed the new method to identify the six varieties of jujube leaf diseases i.e. jujube fruit rust disease, jujube rust, jujube white rot, jujube anthracnose, ascochyta spot of jujube, jujube witches broom based on color, texture, morphological features and classified using neural networks. Firstly, after image acquisition nine colors, eleven texture and five morphological features are extracted corresponding to the red, green and blue plane of the image. Best twelve features using step wise discriminant analysis (STEPDISC) and four principal components using Principal Component Analysis (PCA) are selected from the original 24 features space. Furthermore, cross validation is performed for each feature set space. In the last stage, a two layer tan sigmoid model using 12 parameters diagnose the jujube diseases. The authors concluded that the detection precision of jujube white rot disease is the highest, due to big diseases spots. The high similarity structure index between jujube diseases decreases the classification accuracy.

Pranjali Vinayak Keskar et al. [41] suggested leaf disease analysis and recognition method for the assessment of injured leafs and classifying the category of diseases. To enhance the quality of acquired images, image enhancement methods were applied. The proposed model is involved with four stages: first stage includes transformation of RGB to the HIS color space, analyzing the histogram and intensity adjustment by applying the thresholding. Further next stage, contains adaption of fuzzy feature algorithm to segment image with adjustable parameter to fit the application in concern. In the third stage, features are extracted using component labeling based on color, size and shape of the diseased spots. The fourth stage is classification, which includes artificial neural networks to categorize disease category. The author concluded

that the proposed model clearly differentiates between healthy and diseased leaves with maximum accuracy rate.

S. Sannakki et al. [71] proposed the organization model to classify grape leaf diseases using neural networks. Initially, the grape leaf image with complex background is captured and the background is removed using green color pixel masking and the noise is removed with the help of anisotropic diffusion up to 5 iterations to preserve the infected part information. K-means clustering is used for segmentation and the textural information from diseased part of the segmented image is calculated from GLCM matrix for nine features. The extracted features are used by Feed forward BPNN for its classification. The author concluded that the maximum accuracy is attained using the hue features only.

Suhaili Beeran Kutty et al. [46] discussed the method for the classification of downy mildew and anthracnose diseases of watermelon leaf using neural network study with respect to RGB color component mean values. Few samples of the infected leaves are assembled and taken with digital camera with detailed calibration process under controlled lightning conditions. Using identified region of interest, RGB color pixel indices are extracted. The suggested classification technique considers the procedure for categorization of disease neural network pattern recognition toolbox in MATLAB and statistical package for the social sciences (SPSS). The authors concluded that the proposed system provides satisfactory results but the CMYK, HSV and HIS can be used as an input in order to increase the efficiency.

Kholis Majid et al. [48] has established a portable presentation for paddy malady diseases identification system, using Probabilistic neural system and fuzzy entropy classifier that keeps running on versatile Android working system. It recognizes specific brown spot, leaf blast, tungro and bacterial leaf blight. After capturing images significant features are extracted, using fuzzy entropy with membership functions for extracting the membership of brightness levels. After feature extraction by using the extracted features, probabilistic neural networks method is used for further classification. The authors concluded that PNN approach provides optimal result, but the tungro disease has the lowermost accuracy of recognition, because certain features of tungro diseases are alike to bacterial leaf blight diseases. But proposed method accuracy can be increased by increasing the dataset.

Revathi et al. [68] demonstrated a new method for the detection of cotton diseases using improved PSO feature selection technique which implements skew divergence method with parameters like variances, texture, color and edge to excerpt the required features. Color variance feature is evaluated using color histogram and color descriptor. The Sobel and Canny edge detection method is used to extract shape Skew divergence feature and texture feature is measured by texture descriptor and Gabor filter. The cross information gains depth, forward neural network (CIGDFNN) supports to distinguish and classify cotton leaf spot diseases such as root rot, leaf blight, micro nutrient, verticilium wilt, bacterial blight and fusarium wilt precisely diminishing the error rate.

Sachin B. Jagtap et al. [36] presented an integrated image analyzer with in a diagnostic expert system model which detected diseases based on color, size, and shape. Histogram analysis is used to increase contrast of image by adjusting its intensity for image enhancement. After image enhancement and color transformation from RGB to HIS color space fuzzy c means clustering is used for identifying region of interest by setting all the important parameters, such as feature of dataset, optimal no. of clusters and degree of fuzziness. Finally, the author effectuated that due to the integration of this proposed system diagnosis, the accuracy will increase. Additionally, the proposed system focuses on specific identification disorder which can be further extended to include more

disorders. Such extension of the system is carried out in such a way that it will be capable of detecting and identifying abnormalities on the other parts of plants also e.g. fruit, stem and root.

J.W. Orillo et al. [59] projected a technique to detect rice plant diseases such as bacterial leaf blight causing brown spot on the leaf using Otsu thresholding method and neural networks. At the first stage, after transformation of RGB to HSV color space, diseased area of the leaf is evaluated using Otsu thresholding method as in a gray level histogram, which has been resulting from the perspective of discriminant analysis. After segmentation, there are four features namely, (a) segment enclosed by the disease on the leaf (b) R, G, and B means value of the disease (c) R, G, and B standard deviation values (d) H, S and V mean values of the disease. In the last stage, back propagation neural network is used to evaluate the accuracy and performance of proposed method. The author finally verified that representative lesions of the diseased leaf are recognized accurately. Table 6 represents the summarization of neural networks techniques used for disease classification.

4.4 Diseases classification using Naives Bayes classifier

This section describes the review of various techniques used for the classification of diseases using Naives Bayes classifier.

Aduwo et al. [3] presented an automated vision based analysis system to detect cassava mosaic disease, based on color and shape features and classify using different classifiers. The procedure begins with the capturing of the leaf images with a standard digital camera. Then, three techniques were used to attain representative feature data from the leaf images of the health plants. For first dataset, to extract color features normalized histogram of the HSV color of hue pixels are evaluated. While shape features are extracted using SURF and SIFT methods for two other dataset of cassava leaf. The image is either classified as healthy or diseased, based on other methods like a k-nearest neighbor classifier (KNN), Naive Bayes and SVM. A comparison of the different classifiers is done and results for the three main datasets were produced and Naives Bayes provided the best results. The author concluded that the study of the color histograms by the use of divergence procedures has the ability to give good classification of the performance by using histograms, because they are more naturally represented as distributions. The extra information in the augmented feature sets lead to better generalization of the classifiers using them.

Dhiman Mondal et al. [55] proposed a technique to detect yellow vein mosaic virus disease in okra leaf with combination of k means and Naive Bayes classifier. Initially twenty three features are evaluated using gray image and converted into the size of invariant features by representing different features range into a standardized feature range. Using gray level co-occurrence, matrix texture features are extracted in the second phase. After feature extraction, Pearson correlation coefficient method is used to identify dominant features. Feature values analogous to dominant feature set are designated to create a feature matrix and clustered using K-means algorithm. The final classification is done using Naive Bayes classifier. The author concluded that the proposed method, identifies 87% diseases correctly and classification rate can be increased using more appropriate features. Table 7 represents the summarization of Naives Bayes used for disease classification.

Table 6 Summarization of neural networks techniques for diseases classification

Proposal	Culture	Diseases	No.of images consider	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/standard dataset
Kuo-Yi Huang et al.[34]	Phalaenopsis seedling	Bacterial [bacterial soft rot, bacterial brown spot, Phytophthora & black rot]	289 images	89.6% With classifying diseases 97.25% without classify diseases	Texture & color	TIFF format	Controlled lighting conditions	Color camera (XC-711, Sony, Japan). Dataset provided by Taiwan Sugar Research Institute, Tainan
Noor Ezan Abdullah et al. [1]	Rubber tree leaf	Corynespora, frog eye & Collectotrichum	800 Images	96.5%	Color	Jpeg format	Controlled lighting conditions	FinePix 6900 Zoom (Fuji Film) digital camera. Samples collected from nursery in Lembaga Getah Malaysia, Nikon COOLPIX P4digital camera. Images collected from different parts of East, Midnapur, India
Santanu Phadikar et al. [60]	Rice leaf	Leaf brown spot,Rice blast, Sheath rot & brown spot	300 Images	94.21%	Features extracted w.r.t zooming algorithm	Jpeg format	Controlled lighting conditions	Nikon COOLPIX P4digital camera. Images collected from different parts of East, Midnapur, India
Dheeb Al Bashish et al. [12]	Leaf & stem diseases	Early scorch, cottony mild, ashen mold, tiny whiteness & late scorch	192 images	93% (approx.)	Texture	Jpeg format	Controlled lighting conditions	Common digital camera. Images taken from Al-Ghor area in Jordan
H. Al. Hiary et al. [4]	Various plants and fruits leaf	Early scorch, Cottony mold, Ashen mold, late scorch & tiny whiteness.	192 images	94.67%	Color & texture	N/A	Controlled lighting conditions	Common digital camera. Images taken from Al-Ghor area in Jordan
Wanrat Abdullakasi-m et al. [2]	Cassava leaf	Brown spot	160 images 5270 blocks[healthy]	79.23% (diseased) 89.92% (healthy)	Color indices	N/A	Natural lighting conditions	Common digital camera. Samples are collected from Kamphaengsaten Camus at Kasetsart University, Nakhon Pathon,Thailand.
Song Kai et al. [52]	Maize leaf	Diseases spot	2410 blocks [unhealthy] 40 images	98% or more	Texture	N/A	N/A	N/A

Table 6 (continued)

Proposal	Culture	Diseases	No. of images consider	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/standard dataset
D.S.Guru et al. [30]	Tobacco leaf	Anthracnose & frog eye	100 images	88.593%	Texture	Jpeg format	Captured in field under uncontrolled lighting conditions	Sony digital camera. Images captured at Central Tobacco Research Institute (CTRI), Hunsur, Karnataka, India
Tushar H Jaware et al. [37]	Leaf	Early scorch, cottony mold, late scorch, ashen mold & tiny whiteness	N/A	N/A	Color & texture	N/A	N/A	N/A
Weidan Zhang et al. [90]	Jujube leaf	Jujube rust, jujube anthracnose, jujube white rot, jujube fruit rust disease, ascochyta spot of jujube and jujube witches broom	300 Images	Jujube rust [91%] jujube anthracnose [89%] jujube white rot [94%] jujube fruit rust disease [84%] ascochyta spot of jujube [73%] jujube witches broom [81%]	Color, morphological & shape	Jpeg format	Controlled lighting conditions	Canon camera (Model 60D)
Pranjali Vinayak Keshar et al. [41]	Various plant leaf	Citrus canker	N/A	N/A	Color	Jpeg format	Controlled lighting conditions	Common digital camera
Sanjeev S Sannakki et al. [71]	Grape leafs	Downy mildew, powdery mildew & anthracnose	33 images	100% (using only hue features)	Texture	Jpeg format	Controlled lighting conditions	Nikon Coolpix P510, 16.1 Megapixel and
			200 images		Color	Jpeg format		Nikon D80 digital camera

Table 6 (continued)

Proposal	Culture	Diseases	No.of images consider	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/standard dataset
Suhaili Beeran Kutty et al. [46]	Watermelon leaf	Downy mildew & anthracnose		75% [Downey Mildew] 76.9% [Anthracnose]			Controlled lighting conditions	
Kholis Majid et al. [48]	Cassava leafs	Cassava Mosaic Disease	N/A	91.46%	Fuzzy entropy	Jpeg format	Images are captured in fields	Mobile camera phone. Images are captured from Laladon, Bogor, West Java, Indonesia
Revathi et al. [68]	Cotton leafs	Grey mildew & bacterial blight	390 images 270 [training] 120[testing]	94%[EPSO]	Color, texture & feature vector using skew divergence method.	N/A	Controlled lighting conditions	Nokia mobile camera. Images are captured at south zone of Tamil Nadu at Andhriyaur district, India
Sachin B. Jagtap et al. [36]	Crop leafs	Leaf batches	N/A	N/A	Morphological	Jpeg format	Controlled lighting conditions	Common digital camera
J.W. Orillo et al. [59]	Rice leaf	Bacterial blight	134 images	100%	Mean and standard deviation	Jpeg format	Controlled lighting conditions	Common digital camera. Images captured at Greenhouse of the International Rice Research Institute located at Los Banos, Laguna, Philippines.

Table 7 Summarization of Naives Bayes techniques for diseases classification

Proposal	Culture	Diseases	No.of images	Accuracy	>Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Aduwo et al. [3]	Cassava leaf	Cassava Mosaic Disease	193 images	N/A	Color and shape	Jpeg format	Controlled lighting conditions	Camera phone, Images captured at Namulonge Crops Resources Research Institute, Uganda
Dhiman Mondal et al. [55]	Okra leaf	Yellow Vein Mosaic Virus diseases	79 images 40 [training] 39 [testing]	87%	Texture	N/A	Controlled lighting conditions	Digital color camera

4.5 Diseases recognition and classification using fuzzy logic analysis

This section describes the review of various techniques used for diseases classification using Fuzzy classifiers.

Azmi et al. [15] presents an orchid diseases detection system using combination of image processing and fuzzy logic. The proposed scheme comprises of two phases; in the first phase, the leafs are segmented using Otsu thresholding methods. After segmentation the area and the number of the diseased spots is calculated. In the second phase extracted diseased spots and area are used as the input of fuzzy logic system. The number of diseased spots for each leaf is stored in a matrix of number during the batch processing of images. Based on these two features, fuzzy system determines the diseases category using nine ‘if-else’ rules based on inputs using Mandani method. The defuzzification is done using the center of maximum method, the mean of maximum method and the center of area method. The author concluded that this method did not provide the actual number of diseases spots. They detect more number of diseased spots as compared to the actual one.

Billah et al. [14] suggested a model for recognizing tea leaf diseases, which uses color wavelet features and adaptive neuro fuzzy inference system. After processing, color wavelet features based on the combined information from both color and texture fields of the image with the second order statistical representation of the wavelets transform are extracted. The extracted features classified by Adaptive Neuro Fuzzy Inference System (ANFIS) along with the three types of disease categories. The author concluded that the proposed techniques gives promising results and can recognize the diseases accurately. The color wavelet analysis performs better than other feature extraction methodologies.

K. Muthukannan et al. [56] defined a fuzzy rule-based technique using color features for the disease classification of tomato leaf. Firstly, gradient operator is used for preprocessing to suppress noise or small fluctuation in the image. Two important features i.e. mean and standard deviation are extracted from cropped image with different image size samples. In the last, Fuzzy Inference System using fuzzy rules with selected color features classified the image region as healthy, slightly healthy and highly affected disease portion of the plant leaf. Where, orange color indicates healthy portion of the image, yellow and red color indicated the diseased region of the leaf.

The author concluded the performance of fuzzy rule based classification is satisfactory. The experimental results show the proposed method can detect leaf diseases with little computational effort. Table 8 represents the summarization of fuzzy logic analysis used for disease classification.

4.6 Diseases detection and classification using PSO

This section describes the review of technique used for diseases classification using PSO.

Zhang et al. [91] proposed an improved PSO algorithm and neural networks to recognize and diagnose maize leaf diseases. Image is enhanced using the histogram equalization method and de-noising is realized using image filters. Color, texture and shape features based on HSI (hue-saturation-intensity) color components are extracted. An improved PSO algorithm based on opposition learning method is proposed to decrease the prospect that the exploration for particle swarm falls into the local optima so as to achieve a more optimal solution. To achieve high convergence speed, more compatible particle obtained to continuously optimize the global area to increase neural network analytical model accuracy. The authors concluded that

Table 8 Summarization of fuzzy classification techniques for diseases classification

Proposal	Culture	Diseases	No. of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Muhammad Thaqif bin Mohamad Azmi et al. [15]	Orchid leaf	Black spots, virus & yellow spots	80 images	N/A	Centroid, area, diseased spots	Jpeg format	Fixed lighting conditions	Digital color camera
Mustain Billah et al. [14]	Tea leaf	Virus & fungal	75 images 45[Training] 30[Testing]	95.7%	Color wavelet feature extraction	N/A	N/A	Digital color camera
K. Muthukannan et al. [56]	Tomato leaf	Early blight, late blight & septoria leaf spot	100 images	95%	Mean, standard deviation	N/A	N/A	N/A

traditional neural networks have slow convergent speed, easy getting into local minimum and low rate of correct motion pattern recognition. The results show more effectiveness than existing ones.

Muthukannan et al. [57] stated the importance of particle swarm optimization based segmentation of images for plants leaf diseases identification. After data set collection, Gaussian filter is used to remove the unwanted information of speckles. The results of preprocessing are analysed using PSNR and Max error parameters. The segmentation is achieved using binary PSO to select the best number of clusters and the centers of the selected clusters are refined by k-means clustering. The PSO is employed for allocating each pixel to a cluster. After segmentation, hybrid feature parameters based on texture, color and shape using GLCM matrices are extracted on the basis of which leaf diseases are classified. According to authors, hybrid feature extraction approach is useful for plant leaf disease classification in terms of reduction of misclassification and also increases the correct prediction classification accuracy. Table 9 represents the summarization of PSO techniques for disease classification.

4.7 Diseases detection and classification using membership function

This section describes the review of various techniques used for diseases classification using membership function.

Anthony et al. [6] presented framework to recognize paddy diseases using membership functions. The color images captured by digital camera in the laboratory with dark background are used to avoid the effect of environmental factors. The images are then transformed into CIE XYZ color space and using appropriate threshold value, images were segmented and edges detected using sobel method. Texture and shape features are extracted by considering the parameters like area, roundness, shape complexity etc. Using these features, membership functions are calculated and defined for each class of disease for disease recognition and classification using nearest neighbor. The author concluded that proposed work gives satisfactory results with less recognition time but noise affects the performance. Table 10 represents the summarization of membership technique used for disease classification.

4.8 Diseases classification using combination of classifiers

This section describes the review of various techniques used for diseases classification using combination of classifiers.

Tian et al. [80] proposed a system that utilizes stacked generalization structure to combine the classification decisions attained from three kinds of support vector machines (SVM) classifiers rather than using single SVM classifiers to identify wheat leaf disease. The leaf region is segmented by using simple threshold method. Color, texture and shape features are extracted and used as training set for three corresponding SVM classifiers. Later on, different extracted feature sets are classified by the classifiers in low level and mid-level categories, which are partly described by the symptom of crop diseases according to the knowledge of plant pathology. Then the mid-level features are extracted from mid-categories produced from low-level classifiers. Finally high-level SVM trained and correct errors made by the color, texture and shape features. The author concluded that compared with other classifiers for wheat leaf diseases recognition, the proposed approach can obtain better success rate of recognition.

Table 9 Summarization of PSO techniques for disease classification

Proposal	Culture	Diseases	No.of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ Standard dataset
Zhiyong Zhang et al. [91]	Okra leaf	Yellow vein mosaic virus disease	400 images	93.3%	Color, shape & texture	Jpeg format	N/A	Images collected from Hebei agricultural university
K. Muthukannan et al. [57]	Tomato leaf	Late blight, septoria leaf spot, down mildew, blast & rust teak.	N/A	N/A	Texture	N/A	N/A	N/A

Table 10 Summarization of membership technique for disease detection and classification

Proposal	Culture	Diseases	No.of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
G. Anthonys et al.[6]	Rice	Rice blast, rice sheath blight and brown spot	50 samples	70%	Color, texture and shape	Jpeg format	Controlled lighting conditions	Digital color camera

El Massi et al. [50] proposed an approach using serial arrangement of two neural networks classifiers. Firstly, images are transformed from RGB to LAB color space. Then images are segmented using *k* means clustering to extract the lesion region. Based on color, first classifier evaluates difference between classes. The damages having a same or an adjacent color are considered in the same class. Then according to the shape and texture features, second classifier is used to find difference between the classes. The method is verified on four categories of diseases, including two categories of pest insects (i.e. Leaf miners and the caterpillar *Tuta absoluta*), and the symptoms of two fungal diseases (i.e. internal powdery mildew and downy mildew). The author concluded that the proposed approach using serial classifiers arrangement method is stimulating and can resolve the difficulties of the individual classifiers.

Es-saady et al. [22] presented a system on serial grouping of two SVM classifiers. Firstly, images are transformed from RGB to LAB color space. Then images are segmented using *k* means clustering to extract the lesion region. Based on color first classifier, the difference between the classes is evaluated. The damages having a same or an adjacent color are considered in the same class. Then, according to the shape and texture features, second classifier is used to evaluate the difference between classes. The technique is verified on four classes, with the damages of six classes of plant leafs diseases. The author concluded that proposed system using serial classifiers combination is interesting, and can resolve the difficulties of the individual classifiers and can be improved using relevant features. Table 11 represents the summarization of combinations of classifiers used for disease classification.

4.9 Diseases classification using orthogonal locally discriminant projection algorithm (OPDPA)

This section describes the review of technique used for diseases classification using orthogonal locally discriminant projection algorithm.

Zhang et al. [87] presented orthogonal locally discriminant projection algorithm to classify the maize plant diseases. The original leaf images are pre-processed and then converted from RGB color space to HSI color space. After that, the green pixels are masked and removed to obtain the non-green component to achieve the useful segment. Finally, every processed image is symbolized as a point in the vector space. Segmentation is done using gray level selection thresholding method. Afterwards, the training data is constructed from the transformation matrix and is assign to low-dimensional feature subspace which is orthogonal locally discriminant projection with respect to the test data points. The nearest neighbor graph weights are adjusted according to their reliability between two nodes. The final results prove that the proposed method is achievable and effective. The effectiveness of kernel space in the OLDPA need to be more examined. Table 12 represents the summarization of technique used for diseases classification using orthogonal locally discriminant projection algorithm.

4.10 Diseases classification using minimum path evaluation theory

This section describes the review of various techniques used for diseases classification minimum path evaluation theory.

Pixia et al. [62] suggested a novel scheme based on minimum distance to identify the cucumber leaf diseases. The leaf images are preprocessed using median filtering, image smoothing and segmented using the color range of different diseases to attain lesion segment.

Table 11 Summarization of combinations of classifiers for disease classification

Proposal	Culture	Diseases	No. of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Yuan Tian et al. [80]	Wheat leaf	Powdery mildew, leaf rust, leaf blight & puccinia striiformis	800 samples 3 fold cross validation	95.16%	Color, texture & shape	N/A	Natural lighting conditions	Nikon D80 camera
Ismail El Massi et al. [50]	Vegetables crops leaf	Leaf miners caterpillar, Tuta absoluta, downy mildew & powdery mildew	200 samples	Class of whites = 94% Class of yellow = 93%	Color, texture & shape	N/A	Controlled lighting conditions	Digital color camera
Youssef Es-saady et al. [22]	Vegetables crops leaf	Leaf miners, Thrips Tuta absoluta, Early blight, Late blight & powdery mildew	284 samples	87.80%	Color, texture & shape	N/A	Controlled lighting conditions	Digital color camera

Table 12 Summarization of technique of diseases classification using orthogonal locally discriminant projection algorithm

Proposal	Culture	Diseases	No.of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ Standard dataset
Shanwen Zhang et al. [87]	Maize leaf	Fungus and leaf spots	100 samples	94% (approx.)	orthogonal locally discriminant feature space	Jpeg format	N/A	N/A

The features are extracted using morphological, texture and color feature extraction method. Thirteen important features are extracted and normalized. Finally, the classification is done calculating the shortest distance path method to evaluate the distinguishing value of disease samples and an average center distance among diseases. As the recognized diseases are more similar with standard diseases, the distance is assumed to be less. The authors concluded that the characteristics based on the minimum path evaluation are very effective. Table 13 represents the summarization of minimum path evaluation theory used for disease classification.

4.11 Diseases detection and classification using fractal dimensions

This section describes the review of various techniques used for diseases classification with fractal dimension and chaos theory.

Da-Ke et al. [85] proposed technique to recognize leafminer infected leaf based on fractal dimensions. Two different kernels i.e. polynomial based kernel function and radial based kernel functions are considered for classifying models. Fractal dimension of the damaged cucumber leaves are applied to the threshold method and support vector machine for reorganization and classification of leaves. Where, fractal dimension provides a quantitative index of the roughness diseased leaf image. Finally, radial kernel based SVM excels to the polynomial-based kernel. The author concluded the recognition and precision are depends on the input vectors. The threshold method is good only for linear problems.

V. Surendrababu et al. [77] defined a method for distinguishing rice leaf disease with fractal dimension and chaos theory. The study of an unhealthy leaf is carried out with respect to its fractal dimension, image pattern, especially box-counting ratio calculation, and chaos to recognize the unhealthy outline self-similarity to reconstruct the fractal. The fractal pattern for the unhealthy leaf at the concluding phase will have the similar pattern during the preliminary phase for each category of rice leaf disease because of self-similarity. The author concluded that the proposed method evaluating the initial information for the progress of an early detection system or for emerging information based expert system. Table 14 represents the summarization of the fractal dimension, and chaos theory used for disease classification.

4.12 Diseases classification and identification using support vector machine (SVM)

This segment describes the review of various techniques used for diseases cataloging using Support Vector Machine (SVM).

Table 13 Summarization of minimum path evaluation theory used for disease classification

Proposal	Culture	Diseases	No.of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ Standard dataset
Dong Pixia et al.[62]	Cucumber leaf	Downy mildew, powdery mildew & anthracnose	N/A	More than 96%	Color, shape & texture	N/A	Controlled lighting conditions	Digital color camera

Table 14 Summarization of the fractal dimension, and chaos theory used for disease detection and classification

Proposal	Culture	Diseases	No.of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ Standard dataset
Da-Ke et al. [85]	Cucumber	leafminer	95 images 61[training] 34[testing]	90%	Fractal dimensions	N/A	Controlled lighting conditions	Casio EX-Z3 camera. Images collected at,China
V.Surendrababu et al.[77]	Rice leaf	Bacterial	N/A	More than 96%	Color, shape & texture	N/A	N/A	N/A

Meunkaewjinda et al. [51] proposed a self-organizing feature map to distinguish the color images of the grape leaves. Before extraction color of grape leaves, anisotropic diffusion method is used to maintain the information of affected pixels. The resulting color pixels are assembled by the modified unsupervised self-organizing feature map and a genetic algorithm to optimize and obtain group of different colors in the image. In the next phase, Gabor filter is applied on segmented images to analyze diseases more efficiently. Subsequently, the support vector machine is applied to categorize grape leaf diseases. The authors concluded that the appearance of grape leaf disease features using proposed method can achieve a very efficient quality of classification, but there are certain restrictions with respect to the background of the image, regarding extraction of indistinct color pixels.

Youwen et al. [86] suggested a technique to recognize two diseases namely powdery mildew and downy mildew that can appear in the cucumber leaves. Statistic pattern recognition approach is used to segment healthy and diseased regions of leaves. To differentiate diseased varieties color, texture and features are extracted. Using all the features, SVM performs the final classification using multiple kernel functions such as linear, polynomial, radial basis and sigmoid function. The authors concluded that using radial basis kernel function with only one shape feature, SVM can recognize cucumber diseases accurately. While with the linear kernel function, combination of two feature sets (texture and shape) provides good performance. SVM has more diseases recognition accuracy and high speed as compared to BP artificial neural network in same environment.

Jian et al. [38] explained the method to identify the diseases in cucumber leaves using SVM with a polynomial function, radial basis function and sigmoid kernel function. The classifier is trained using the above mentioned kernel functions and results were compared to decide the best kernel function for identification of diseases. The author summarized that the radial basis function is the best method to classify leaves diseases and promises good accuracy to identify diseases but this method is preferred when the leaves are affected by a single disease. This method cannot diagnose accurately when two or more diseases occur simultaneously.

Asraf et al. [9] introduced the method to detect the symptoms of the oil palm leaves nutrient disease using support vector machine along with polynomial kernel with hard margin, polynomial kernel with soft margin, and linear kernel. Color and histogram based texture features (based on RGB color and gray level co-occurrence matrix) are extracted and separated into numerous sub-features. SVM classifier is then used for classification using all 27 extracted features using different kernel functions. After, classification, a polynomial kernel with soft margin is more proficient of accurately classifying nutrient disease according to its class as compared to other methods. The author finally deduced that more accurate results can be attained using proper kernel trick function.

Lu et al. [20] proposed a novel technique to recognize the maize leaf diseases, based on fuzzy least square vector machine (FLSVM) algorithm. Using YCbCr color space, spatial GLCM is used to calculate texture characteristics of maize leaf. After feature extraction, fuzzy least square vector machine is used for categorization. Where, the sample mean is calculated with respect to the center of each class. Then according to the distance between center (sample class) and sample, it calculates the initial membership function using fuzzy K nearest neighbor method. It requires membership function to be accurately reflected the distribution characteristics of the samples. The author concluded that proposed model provides encouraging results. It gives smaller errors in the identification process when the samples number is too small. The developed FLSVM also gives prediction uncertainty.

Arivazhagan et al. [7] discussed a system for automatic plant disease detection, which comprised of four stages. In the first stage, a color conversion space is created for the RGB image and then using specific threshold value green pixels are masked, removed and monitored by the segmentation process. Using co-occurrence matrix texture features are calculated for useful segments. Finally, the useful features are handed over to SVM classifier where classifier gain is obtained by the minimum distance criterion. The results specify that the proposed technique can distinguish and classify leaf diseases with a minimalistic computational effort. The author envisioned improving the disease identification rate along with color and texture features for any given input conditions.

Zhou et al. [93] explained an approach which focused on cercospora leaf spot identification in sugar beet using support vector machine with hybrid algorithms of template matching. The technique divided in three stages. Firstly, to discriminate leaf parts from the soiled background for automatic collection of initial sub-templates a plant segmentation index of G-R is introduced. Secondly, a robust template matching technique is implemented for constant monitoring of foliar translation, dynamic object examining and disease development. At last, SVM used for disease classification using color features. Ultimately the author analyzed that the segmentation process is not suitable for other Dicot family plant.

Ratnasari et al. [66] explained a model to identify the sugarcane leaf diseases and recognize severity of spot disease based on segmentation spot. Severity measurement is accomplished only on sample data consisting of regular sized leafs. Disease identification is achieved through segmentation of diseases spot using thresholding of a^* component from $L^*a^*b^*$ color space. After segmentation using GLCM, texture and color features are extracted. In the end, SVM classifies the various sugarcane leaf diseases (i.e. ring, rust and yellow spot) using extracted features through the use of different kernels such as polynomial with third order, quadratic, radial basis function (RBF) and linear function. The author effectuated that the proposed model displays more accuracy in classifying sugarcane leaf disease with small average error severity calculation. Linear kernel function gives better results than others. On the other hand, due to limitations of segmentation techniques, lesion cannot be identified accurately.

Mokhtar et al. [53] applied Gabor wavelet transform technique to extract various diseases in tomato leaf. Various relevant features along with SVM having different kernel functions are used to identify and recognize different kind of disease that infects the tomato plant. Initially, a wavelet based feature technique is used to identify an optimum feature subset. Finally, SVM classifiers with different kernel functions such as the Cauchy kernel, Invmult Kernel and Laplacian Kernel were employed to identify and detect tomato leaf infected with powdery mildew or early blight. Finally, it is concluded that the Cauchy and Laplacian kernel functions provides good accuracy but the choice of optimum factors of kernel functions is still one of the critical issue.

Zhang et al. [89] explained a new methodology to advance the recognition rate of diseases in cucumber leaf using singular value decomposition. Watershed algorithm is used for segment spot from leaf images in the first phase. In the second phase, every spot is distributed into little blocks, and combining features of global local singular values are extracted from each block by SVD. In the third phase, main point vectors are assembled and their dimensionalities are adjusted. Finally, SVM classifier is used to identify the category of the unknown disease leaf image. The author concluded that presented method achieve good result. The main limitation of the proposed method is that it needs more computation efforts to evaluate the singular values and advanced color features can improve a better recognition results.

Qin et al. [64] investigated a system for the analysis and classification of the four categories of alfalfa leaf diseases. Using artificial cutting from every captured diseases image, a sub image with single or multiple typical diseases are achieved. Every sub images are transformed into HSV color space and L^*a^*b color space. In each pixel in the sub-image, (a^*) component value and the (b^*) component value were regarded as the color features of the pixel. All pixels in the image were clustered into ten classes. After all pixels in a sub-image are clustered into ten classes using a clustering algorithm, the mean of the H components of all pixels in each class is calculated. Then using twelve lesion segmentation methods combined with clustering techniques (i.e. fuzzy C-means clustering K-means clustering and K-median clustering) and supervised classification algorithms (i.e. Naive Bayes algorithm logistic regression analysis, linear discriminant analysis and regression tree) used to segment the sub images. The pixels in the class with the minimum mean were treated as typical lesion pixels, and the pixels in the seven classes with the largest means were treated as typical healthy pixels. From the lesion images based on color, shape and texture total 129 feature are extracted. Using ReliefF, IR and correlation based feature selection methods useful features are selected. Finally diseases recognized and classified using three supervised learning models using support vector machine, random forest and K-nearest neighbor. Evaluations of the classification results of the learning models are evaluated. The author concluded that the SVM model using most significant 45 features is the optimal model. Table 15 represents the summarization of support vector machine techniques used for disease classification.

4.13 Diseases classification using discriminant analysis

This section describes the review of various techniques used for diseases classification using discriminant analysis.

Bandi et al. [10] suggested a technique to classify four classes of citrus leaf diseases i.e. normal, greasy spot, melanose and scab. Based on the color co-occurrence method texture features are evaluated for each citrus leaf sample. After extracting features, they are classified with leaf age condition using Naive Bayes classifier (NBC), Linear Discriminate Analysis (LDA) classifier, k-Nearest Neighbor (kNN) and Random Forest Tree Algorithm classifier (RFT). Eventually using earphone operative characteristics contour all the classifiers are compared. The author concluded that Normal leaves and Greasy spot leaves can be classified easily from the other classes of leaves. Whereas, Melanose diseased leaves classification rate is less. The LDA outperforms than other classifiers.

Kruse et al. [43] studied the classification of each pixel as injured [43] or healthy from images of clove leaves through the extraction of color and texture based information features. The four classification approaches were evaluated as Fit to pattern model approach (FPM) combined with T statistics, linear discriminant analysis (LDA), K means clustering and residual sum of squares for classifying and calculating leaf surface injury. The predicted leaf pixel classification is then compared with manually segmented images. The ground truth (binary mask) is used to evaluate pixel classification accuracy. It is concluded that an LDA classifier performed well as compare to mentioned three methodologies in pixel identification owing to its higher accuracy, precision and less computational time. It is determined that the simple feature vector with only color information is sufficient for leaf pixel injury classification. The spatial information does not increased the computation time

Table 15 Summarization of support vector machine technique used for disease classification

Proposal	Culture	Diseases	No. of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ Standard dataset
A. Meunkaewjinda et al. [51]	Grape leaf	Scab & rust	1478 [training] 115 [testing] Further divided into sub-images	97.8%	Color	N/A	N/A	N/A
Youwen et al. [86]	Cucumber leaf	Powdery mildew & downy mildew	40 images	100%	Texture, shape & color	N/A	Images captured in field	Images collected from field Of cucumber research base of Shenyang Agriculture University
Zhang Jian et al. [38]	Cucumber leaf	Downy mildew, brown spot & angular leaf spot	60 images	RBF provides Best results	Texture, shape & color	N/A	N/A	N/A
H. Muhammad Asraf et al. [9]	Oil palm leaf	Nutrition disease namely nitrogen, potassium & magnesium	420 images 300 [training] 120 [testing]	95%	Color, texture & histogram based	N/A	Controlled lighting conditions	Digital color camera
Cunlou Lu et al. [20]	Maize leaf	Blight, sheath blight & southern blight	Set of images [training] 30 [Testing]	98% or more	Texture	N/A	N/A	N/A
Arivazhagan et al. [7]	Rose, beans, lemon and banana leaf	Bacterial disease, sun burn, early scorch, late scorch & Fungal disease	500 images	94%	Texture	N/A	N/A	Digital color camera. Images collected from Tamil Nadu
Rong Zhou et al. [93]	Sugar beet	Cercospora leaf spot	N/A	99.07% [testing] 99.44% [training]	Histogram	N/A	Controlled lighting conditions	CMOS camera (CMOS130-USB2, Fortissimo Co., Japan)
Evy Kamillah Ratnasari et al. [66]	Sugarcane leaf	Sugarcane ring, rust & yellow spots	A set of images [training] 30 images [testing]	80%	Texture	N/A	Controlled lighting conditions	Digital color camera. Images are collected from sugarcane fields in Indonesia
Usama Mokhtar et al. [53]	Tomato leaf	Powdery mildew & early blight	200 images 10-fold cross validation	99.5%	Texture	Jpeg for-mat	Controlled lighting conditions	Digital color camera
	Alfalfa leaf		899 images	80% approx		N/A		

Table 15 (continued)

Proposal	Culture	Diseases	No. of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Feng Qin et al. [64]		Leaf spot, rust, leaf spot & Cercospora leaf spot			Texture, shape & color		Controlled lighting conditions	Digital color camera. Images taken from Langfang Forage Experimental Base, Institute of Animal Science, Chinese Academy of Agricultural Sciences & alfalfa fields Hebei Province, China

significantly. Table 16 represents the summarization of discriminant analysis techniques used for disease classification.

4.14 Diseases classification using AdaBoost algorithm

This section describes the review of various techniques used for diseases classification using AdaBoost algorithm.

Min Zhang et al. [88] explained a new method using zone based local and global features to identify citrus canker from citrus leaf images. In the first phase, an improved AdaBoost algorithm is used to evaluate the most imperative features (citrus lesions) after extracting the lesions from their background. In the second phase, for combining texture and color information about lesion, a special citrus canker feature descriptor is proposed. To disclose the spatial properties of citrus canker, Local Binary pattern descriptors are used. In the last phase, to identify canker lesion, two-level hierarchical recognition structure is established. The author compared the performance of the suggested method with human experts and concluded that the accuracy of the presented approach is almost similar.

K. Jagan Mohan et al. [52] proposed a system to identify and classify paddy leaf diseases i.e. brown spot disease, leaf blast disease and bacterial blight disease. The proposed work is divided into two parts. Firstly, diseases are identified using HAAR features and classified using AdaBoost classifier to locate the disease affected portion of the paddy plant and provides identification rate 83.33%. Secondly different diseases are recognized using SIFT (Scale Invariant Feature Transform) feature extraction method to extract local features of image and classified using k-NN (k-Nearest Neighbors) and SVM (Support Vector Machine) classifiers with recognition rate 91.10% and 93.33%. The author concluded that this approach can detect the disease at an early stage and thus can minimize the loss of production. Table 17 represents the summarization of AdaBoost algorithm used for disease classification.

4.15 Diseases classification using rule set theory

This section describes the review of various techniques used for diseases classification using rule set theory.

Phadikar et al. [61] proposed a method based on infected region features to classify different categories of rice. To separate the infected segment, Fermi energy segmentation method is used. Using novel algorithm, shape, position and color features, diseases symptoms are extracted. Change in shape, position and color of diseases spot defined as features to classify diseases with respect to boundary of the leaf. Genetic algorithm is used to detect the shape of the infected segment which estimates the structure of the leaf region. The disease spot is separated into different blocks and then settled as a quad tree at different labels. Consequently, the position of infection is determined. Binary illustration of each block decreases computational complication reasonably. To minimize the loss of information and complexity, significant features are selected using rough set theory. Finally, a rule base classifier using selected features has been assembled that cover all rice leaf diseases. The author concluded that proposed algorithm gives superior outcomes as compare to traditional classifiers. It involves lesser computational complexity. Table 18 represents the summarization of rules based theory used for disease classification.

Table 16 Summarization of discriminant analysis techniques used for disease classification

Proposal	Culture	Diseases	No.of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Sudheer Reedy Bandi et al. [10]	Citrus leaf	Greasy spot, melanose and scab	40 images 20 [Training] 20[Testing]	98.75%	Texture	Uncompressed .jpeg format	N/A	Digital color camera
Ole Maths Opstad Kruse et al. [43]	Clove leaf	Leaf injury	72 images	95%	Color & Texture Intensity	TIFF format	Controlled lighting conditions	Canon EOS 20D SLR

Table 17 Summarization of AdaBoost algorithm used for disease classification

Proposal	Culture	Diseases	No. of images	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/Standard dataset
Min Zhang et al. [88]	Citrus leaf	Citrus canker	500 images	88%	Color & texture	N/A	Captured in the field	Digital camera Sony DSCP92 and Canon EOS350D. Images were collected from orange plants in winter in 2005 and 2006 from Guangdong province, China and in spring in 2007 from Guangxi province, China
K. Jagan Mohan et al. [52]	Paddy leaf	Brown spot disease, leaf blast disease and bacterial blight disease	60 images	Identification 83.3% Recognition 91.1%, 93.3%	HAAR & SIFT	N/A	N/A	N/A

Table 18 Summarization of rules based theory used for disease classification

Proposal	Culture	Diseases	No.of images considered	Accuracy	Features	Image format	Environment conditions	Device used for image acquisition/ standard dataset
Santanu Phadikar et al.[61]	Rice leaf	Brown spot, bacterial blight, rice blast and sheath rot	500 images 10 fold cross validation	91.19% [SMO]	Color & shape & position	N/A	N/A	UCI dataset

5 Discussion

Precise and well-timed identification and classification of diseases is helpful to improve the growth. Diseases can be identified by naked eye observation using continuous monitoring experience level. But, it results in high cost as well as time consuming. It has been shown that the image processing proves to be an effective tool for identification and classification of plant diseases, wherein the digital camera functions as a better substitute for the human eye and human brain is superseded by a learning and optimization algorithm. To overcome the difficulties of manual process, several techniques based on computer vision are developed in recent years to identify and recognize disease of agriculture and horticulture crops. The above literature review explained various methods for identification and classification for different plant leaf diseases. Even though the importance of the subject of identifying leaf diseases using digital image processing is tremendous and this has been studied from approximately 25 years, but the advances achieved seem to be a little timid. Some facts lead to this conclusion:

- a) Setup conditions are too firm: The presence of noise in captured images makes the quality analysis very difficult. Another constraint is environment conditions for capturing images in controlled lighting conditions. The implementation of image processing techniques in real world application is problematic for number of issues. Existing techniques exhibit high accuracy while examined under controlled laboratory lighting conditions. However, their use in outdoor condition is problematic, since the accuracy in such conditions is drop dramatically. Robust calibration is required to reduce the effect of illumination, angle of camera, capturing device and distance between objects. The other significant challenge arises due to the inherent variability of color under natural lighting conditions.
- b) Lack of technical knowledge or Selection of image processing schemes: The choice of the image-processing techniques as well as the classification strategies is crucial for the effective performance of any computer vision system. Assessment of segmentation and classification techniques cause problems like oversized sample set, over fitting etc. In some cases, authors do not provide required technical information.
- c) Processing Speed: Processing speed of the detection and classification technique is an important issue as we need to process the huge amount of data. Many feature extraction and selection techniques are proposed to reduce the dimensions of the obtained data firstly and then analyzed for further processing.
- d) Significance of universal approach: It is difficult to develop a universal system which has the capability to detect and recognize every type of plant leaf disease. Most of the techniques or systems proposed by authors are able to deal with only one species of plant diseases. Therefore, there is a need to develop a universal system for the detection of plant leaf diseases.
- e) Complexity of images: Due to complexity of considered image, it is somehow challenging to separate the desired leaf region from the complex image background.
- f) Reliability of data (images): The additional concern is related to the unavailability of complete and reliable information of data. The device classes i.e. lighting set up, camera angle, distance etc. that have been used to produce the results are not fully known. Many of the authors do not provide their testing and training data information, which is the main concern during examine validation of results. It is necessary to provide different reliable measures.

- g) Image quality: For better diseases detection and recognition, high quality images dataset are recommended. The lighting setup must be in proper position because it also can affect the image captured

We concluded that the authors should devote more time in learning and understanding of the tools which they intend to use. Apparently, some authors provide high quality manuscripts, in which they define their work clearly with precise device classes, measurable parameters and used technique and tools.

6 Conclusion and future scope

This paper highlighted the concepts and techniques used by various researchers to identify and classify diseases, challenging issues and problems. The ultimate goal is to limit the impact of plant diseases on agricultural production using image processing techniques. Moreover, it is important to understand the correlation between the diseases symptoms and its impacts on yield. The large number of agriculture and horticulture applications based on the detection and classification of plant leaf diseases make it difficult for someone to prospect all important concepts present in the literature. This is a reason of missing potential solutions for problematic issues. The authors should implement more novel algorithms and understand more concepts about tools to achieve better results. They should provide more reliable results by considering the accuracy and quality parameters, which are needed in this highly competitive and changing industry. A brief discussion of popular detection and classification techniques is provided along with possibilities of extensions. The key findings of our literature can also be investigated and analyzed for the other pattern recognition problems. Based on our key findings from the previous studies, following future aspects can be considered for further research.

- a) In future, the existing algorithms can also be utilized in outdoor conditions along with the combination of leaf front and leaf backs into a common dataset.
- b) Further research can be devoted to model the detection and recognition techniques under mixed lighting conditions. It is of great importance to confirm that the accuracy of classification can be maintained under these conditions or not.
- c) An unexplored combination of feature extraction, selection and learning methods can also be used to increase the effectiveness of detection and classification techniques.
- d) The future work can also be dedicated to the automatic estimation of severity of the detected diseases.
- e) The instant solutions can be made available to the farmers by designing the mobile based applications.
- f) Online solutions related to plants diseases can be provided by using web portals.
- g) It is also required to increase the number of data for training and testing purposes to achieve better accuracy.
- h) Existing work can also be extended to achieve high speed and accuracy by developing the advanced algorithms.

In this review, as there are so many methods are proposed and implemented to identify, recognize and classify plant diseases using digital imaging and classification techniques. The paper presents an overview of technical concepts used in the existing methods related to the

objective of the paper. The plant diseases detection and recognition area of research is not limited to above-mentioned future scope.

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Gitaly Dhingra pursuing PhD (ECE) from Thapar University, Patiala, Punjab, India in the field of image processing and computer vision. Her research interests are video and image processing.



Vinay Kumar received his Post-doc from Universidad Carlos iii de Madrid, PhD from Jaypee University of Information Technology, Solan, M.Tech from Dayalbagh Educational Institute and B.E from Dr. K. N. Modi Institute of Engineering and Technology. His research interests are video and image processing.



Hem Dutt Joshi received his PhD (ECE) from Jaypee University of Engineering and Technology, Guna, in 2012, M.E (CCN) from M.I.T.S, Gwalior affiliated to RGPV, Bhopal, in the year 2004 and B.Tech (ECE) from Barkatullah University, Bhopal in 1999. Currently, he is working as Assistant Professor in Thapar Institute of Engineering and Technology, University, Patiala. His research interests are digital signal processing, wireless communication systems, OFDM, MIMO-OFDM, Antenna designing. He is a life member of the Institution of Electronics and Telecommunication Engineers (IETE), India.