Research Article

Detection and Classification Techniques of Citrus Leaves Diseases: A Survey

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Abstract: Agricultural production is essential to the economic development of any country. That's why disease identification in plants is critical in the agricultural sector, as a disease in plants is a regular occurrence. If reasonable precautions are not taken on time, plants can significantly affect the environment, affecting product quality, quantity, and productivity. Lemons, grapes, limes, oranges, etc., are common citrus fruits grown the entire world. About 50% of citrus fruits are wasted each year because of diverse plant sicknesses. This paper offers a survey of various approaches for detecting and classifying diseases in citrus plant leaves. A comprehensive taxonomy of citrus leaf diseases is also presented. A study of automatic illness recognition and classification methods are also discussed. We explore different methods for pre-processing, segmentation, extraction of features and grouping. Discuss also the relevance of functional extraction and techniques of deep learning.
Keywords: Citrus, disease, detection and classification, deep learning

1. Introduction

Plant infections are the most severe problem which has a significant impact on agricultural production quality. The critical task for economic development is to improve production by identifying and classification plant lesions at an early stage (Gutte& Gitte, 2016). Plants of citrus are infested by scratches such as anthracnose, scab, greening, black spot, melanosis, downy mildew, and canker (Radhika et al., 2008). Citrus fruits have a wide range of fibre, vitamins, and minerals, which means having healthy biological behaviours cautiously correlated with various well-being assistances and inferior the risk of diseases (Boeing et al., 2012). Fruits of citrus have anti-mutagenic and antioxidant effects, which are significant advantages. There are multiple strategies for detecting citrus lesions, including active contour, edge tracking, clustering, watershed, saliency, thresholding, and few others. During all methods, though, the identification mechanism is almost similar. In agricultural sciences, the pre-processing step can be used to achieve the following goals: (1) To distinguish citrus diseases in leaves, fruits, and stems (2) to find a cure of diseases (3) to determine colour and outline of affected areas in plants and (4) to diagnose disease regions in plants of citrus. Segmentation is the process of partitioning the image with distinct meanings for extracting features. The notable picture elements characterize texture, form, and colour properties. Segmentation is a procedure of partitioning the image with distinct meanings for extracting features. Classification is the grouping based on extracted features.

Prajapati et al. (Prajapati et al., 2016) addressed various segmentation and feature extraction techniques, including region-based, threshold-based, edge-based, Principal Component Analysis, and Gabor filter. They used colour segmentation with green pixel masking to remove the shadow and applied Otsu thresholding to the diseased picture. They extracted colour, structure, and texture characteristics and then used a support vector machine classifier to categorize diseases with high accuracy. Revathi and Hemalatha(Revathi &Hemalatha, 2014) looked at ten different plant diseases, including bacterial blot, late scorch, sunburn, fungal streaks, late blight, sooty mould early, and so on. SVM is used to classify diseases based on texture features such as homogeneity, cluster hue, cluster prominence, and contrast.

This survey discussed pre-processing, segmentation, attributes extraction, and disease classification with their threats, strengths, and weaknesses for citrus fruit diseases. The following is how the remainder of the paper is structured: The taxonomy of citrus leaf diseases is presented in Section 2. Section 3 provides an in-depth review of various citrus leaf disease strategies. Section 4 discusses the study. Finally, Section 5 brings the paper to a conclusion.

2. Citrus diseases taxonomy

Diseases in citrus plants are the principal cause of reduced productivity in the agricultural sector, which results in the loss of the economy of any country. Citrus fruits are the prominent producer of vitamins C and A. Citrus diseases, on the other hand, have had a significant impact on production in terms of quality and quantity. Plants of citrus such as grapes, oranges, lemons, and limes are affected by various citrus lesions such as anthracnose, melanosis, greening, canker, scab, and a few others, as seen in Fig. 1, and their symptoms, favorable circumstances in Table 1. The following is a short outline of several citrus diseases.

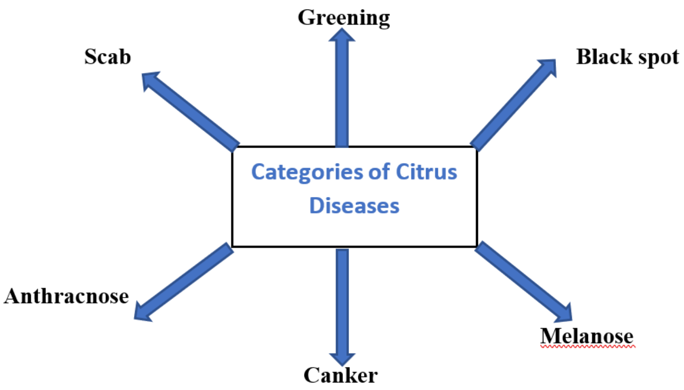

Figure 1. Categories of Citrus Diseases

Canker

Citrus canker disease is a very harmful disease, and it is just cancer in citrus plants; lacerations on citrus plant leaves is the cause. Citrus canker is a bacterial disease that causes citrus plants to produce premature leaves and fruits. The damaged leaves have white spongy patches that can eventually turn grey or brown. On both sides of the stems, spots with oily borders or yellowish rings (lesions) can be seen. The presence of lesions may be used to diagnose this disease in vines(Doh et al. 2019).

Citrus Scab

Scab acne is a combination of bacterial tissues and organisms in citrus fruits and leaves. This acne is often raised in rose to brownish colour. Scab lesions are brown-yellow and grey-dirty(Doh et al. 2019).

Table 1. Indications of several citrus plant illnesses

Illness Name in Citrus	Indications	Favourable circumstances
Anthracnose	Brown or black dot lesions	Cool-weather
Canker	Water-soaked yellow halo boundaries	Spring period
Citrus Scab	On leaves develop tiny, semi-translucent, lesion-like spots.	Summer period
Sooty mould	Leaves blackening	Seasonal
Powdery mildew	White powdery bacteria sometimes form on the upper side	Moist weather, Cool
Black rot	Reddish-brown markings formed on the leaves irregularly	Warm weather and wet weather
Downy mildew	Infested leaves develop steadily browning yellow-green lesions. The leaves plagued often drop prematurely.	Season rainy and summer humid

Anthracnose

Anthracnose is the first pathogen to colonize weakened or elderly tissue. Overwatering,rain spray, anddew arethe reasons for the plants to thrive on stationary copse in the shelter, and they spread a short distance. Citrus leaves have a more or more miniature battleship, rough field, and a brownish colour with a noticeable purple boundary. Furthermore, other causes, including sunburn, chemically extreme heat, insect destruction, and extended storage time, can negatively impact the fruit's appearance. Anthracnose lesion spots are brown and 1.5mm in diameter or larger(Doh et al. 2019).

Black Spot

In black spots, disease plants are susceptible, and the atmosphere is favourable to disease, the black spot in citrus, also known as CBS. Oval, tiny, hazardous spots with grey cubes are the symbols of citrus fruits and leaves. Black spot lesions are dark brown and have a width of 0.12 to 0.4 inches.

Melanosis

It is a saprophyte whose strictness is moderate. The expanse of microorganisms on departed leaves in plants shelter is used to describe it. A tiny brown spot appears on the leaf, which converts into a red-brown gum. The age of the fruit determines fruit signs at the time of infection. On the exterior of fruit and leaves in citrus, the symptoms appear(Sharif et al. 2018).

Greening

Yellow dragon infections, also known as greening, are caused by a bacteria pathogen. Greening infection is hard to manage and replicate in infected plants. Orange, better, and misshapen fruits are produced by the infected plants, making them unfit for sale as fresh fruits or juice. There is no treatment for a plant after it has been infected, and it will die. Weed management, foliar feeding, drainage, sediment fertilizer, and effective psyllid management will help keep plants healthy and profitable(Priya 2016).

3. Recognition and classification of citrus illness

This section contains a thorough outline of image processing procedures in fig. 2 that are used to recognize and categorize citrus diseases. These measures include the use of all citrus fruits and leaves. Automated picture processing procedures consist of four stages: pre-processing, segmentation, feature withdrawal, and classification. Each step has its challenges, strength, and weakness.

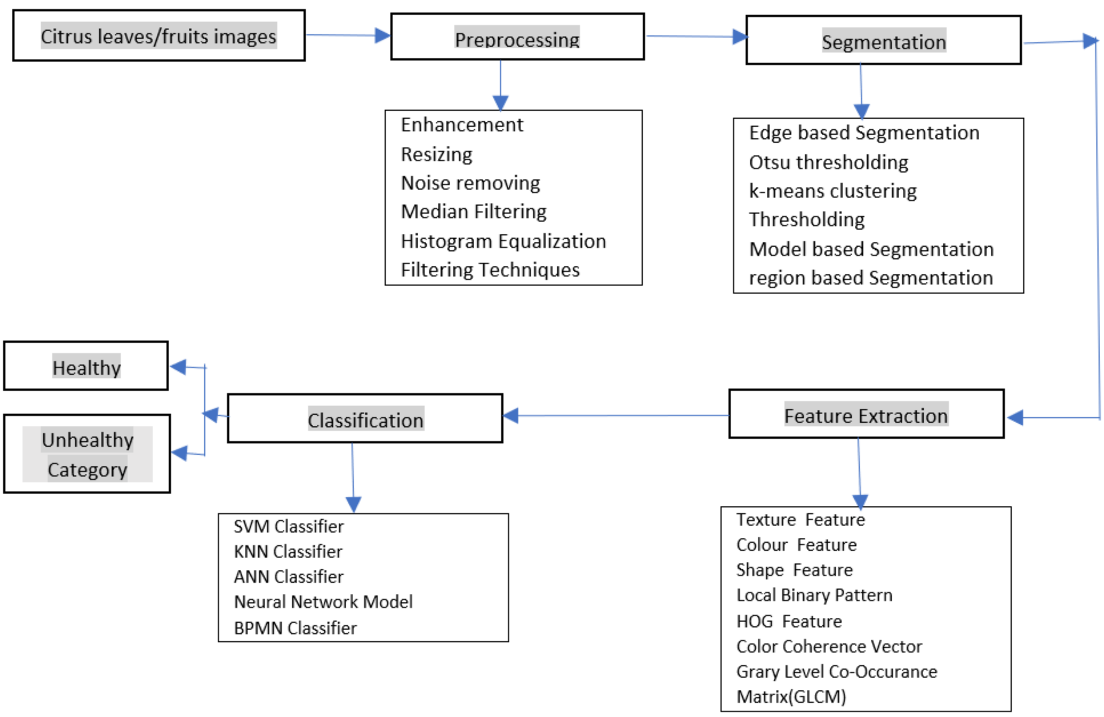

Figure 2. Citrus disease detection and classification techniques

3.1.Pre-processing based techniques

It is pre-processingmeans to improve the input image's optical consistency. This eliminates many problems such as luminosity, lighting, and issues related to weak contrast. Pre-processing is an essential part of the image processing phase since low contrast photographs impair the precision of the lesion segmentation. A hybrid stretching technique related to aGaussian and top-hat filter function is used(Sharif et al. 2018). The top-hat filter is initially made on the inputimage. The laceration contrast can be increased by including the top-hat filter image and the Gaussian-different image shown in Fig 3.

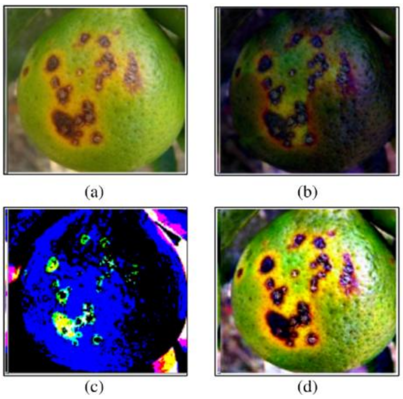

Figure 3. Variance of image enhancement: (a) input image; (b) image after top-hat filter; (c) actual image in Gaussian; (d) enhanced picture(Sharif et al. 2018)

3.1.1. Challenges

Compared to the initial picture, the pre-processing phase makes the disease area in the image more apparent, as in fig. 3. The problems of the pre-processingof images are (1) low-intensityinput images; (2) the noisy foreground from the achene covering;(3) variation in lighting; (4) many associated severances with thousands of diverse frequency ranges; and (5) achieving the best contrast among the background and the fruit covering. These difficulties have a significant impact on the precision of disease segmentation. The literature describes variouspre-processing techniques, includingtop-hat filtering, colour spaces, median filtering, etc.

3.1.2. Picture enhancement

Histogram equalization, colour transformation are examples of image enhancement. For transforming RGB colour space pictures to grayscale, colour transformation is used. For picture clarity, the histogram equalization technique is used(Abdullah et al. 2012). Another approach for detecting plant diseases that use pre-processing methods and a fuzzy logic system to identify the plant's lesions has been suggested. The goal of this study was to find conditions in leaves in watermelon. To remove RGB details from photographs, RGB colour is used. Anthracnose and mildew disease accuracies are 67% and 70%, respectively, according to the method(RAJESH PYDIPATI 2004).

3.1.3. Colour based transformation

Renuka(Kajale 2015) suggested an image pre-processing scheme-based method for automated disease detection. Soft mould, late sign, early fire, slight achromatic colour, and grey mould were among the five diseases studied by the author. There are four main steps of this scheme. Initial photos are captured and converted to HSI colour space transfer in the first step. The green pixel is protected and minimised in a subsequent actionusingactual threshold values. The K-means sequence is for segmentation in the 3rd step, and the features of texture are takeout using SGDM. Thediseases leaves are measured for the texture study(Rumpf et al. 2010). Tushar and colleagues suggested a picture pre-processing-based method for detecting crop leave diseases. The writers chose tiny whiteness Cottony mould, ashen mould, early scorch, and late scorch for this study. To begin, a base image is created and converted to a colour space conversion. The green pixel is masked after segmentation using the K-mean technique. Furthermore, the impacted regions' pixel values are deleted. Finally, using a neural network classifier, the characteristics are extracted, and the system's precision rate is between 83 and 94 percent(Hayat, Abdullah, and Chaudary 2007).

3.1.4. Noise reduction & resizing

(Ying et al. 2009)Noise is removed using simple and median filters, and photographs are segmented into the spot backdrop using thresholding. The disease spots are classified by performing edge detection and snake methods and got higher classification accuracy. (SS et al. 2011)focused on picture pre-processing and machine learning strategies and created a hybrid smart system for detecting diseases in pomegranate fruits. There are four key stages to the system's operation: After capturing the original images with a sensor, pre-processingstrategieslike noise removal,scanning,enhancement, and morphological operations, resizing, segmentation, and others, are implemented. The colour, texture, and shape features are then extracted, and these extracted geographies are then fed into machine learning techniqueslike ANN and getting better classification accuracy(Pujari, Yakkundimath, and Byadgi 2015).

3.2.Image segmentationtechniques

The term "segmentation" refers to the division of a picture into many bits. The most general definition of segmentation is detecting an image's region of interest (ROI). The difficulties in disease segmentation, as well as their meanings, are outlined below.

3.2.1. Challenges

The main goal of picture segmentation in agriculture and other sectors is to distinguish the illness and context parts of the picture. Numerous challenges happen for segmentation of ailment parts in the image, including (1) change of disease colour while doing colour-based segmentation; (2) considerable inconsistency of colours become segmentation procedures complex; (3) change in disease part size; (4) volume of fruits. These issues wreak havoc on disease detection precision and reduce the system's overall efficiency. Below is a brief overview of some common segmentation approaches, such asedge detection, thresholding, and K-means(Iqbal et al. 2018). Table 2 has the strength and weakness of different segmentation approaches.

3.2.2. Thresholding

Thresholding is a straightforward segmentation strategy. The value of thresholding obtained usinga histogram of the input pictures are used to complete the segmentation. As a result, Accurate edge detection will give accuratethreshold values. This technique is ineffective when images are complicated; this is the weakness of this technique.(Zhihua et al. 2013)demonstrated a segmentation technique focused on colour attributes and field thresholding. The characteristics are used to differentiate between infections. Various black limits are used to assess the effectiveness of field thresholding. (Patil and Bodhe 2011) determineOtsu threshold, K-mean clustering and two image processing techniques. As opposed to the Otsu thresholding method, the k-meansapproach produces more significant outcomes. (Phadikar 2012)suggested the use of basic threshold and triangle threshold strategies. Leaf region and affected area are segmented using these techniques. This device has a 98.6 percent overall accuracy(Iqbal et al. 2018).

3.2.3. Edge detection

Researchers like Gradient, Sobel, Canny, Robert, and Laplacian presented many edge detection techniques. Propose an edge identification segmentation(Singh and Misra 2017) method for cotton leaf spot diseases. Picture features like border,texture, colour, and form are calculated after segmentation to categorize the diseased location; these derived features are used by neural network for disease categorization. This classifier recognises wood diseases and differentiates between applications for fungicides. Using an edge detection segmentation strategy, created a method for identifying cotton leaf diseases.

3.2.4. K-means clustering

The segmentation is finished by the K-means clustering method. It divides tainted photos into several clusters. A solitary cluster is a group of picture elements comparable together but separates from the values of other clusters. Dheeb has created a technique for recognizing illnesses focused on segmentation strategies for plant leaves and stems. Initially, input images by the K-means methodology are segmented, and then these segmented pictures are accepted via a NN classifier in the second phase. Five diseases such as late sparrow, cotton mould,slight whiteness, early sparkling, and the ashen mould are obtained for this function. NN classification is applied to the classification through automated identification and accurate assistance of the diseases of the leaves with an accuracy of about 93%(Krishnan and Sumithra 2013). A novel approach has been implemented in(Pujari and Yakkundimath 2013), which identifies the contamination sections of plants by a K-means method. In different clusters, the disease and history regions are described.

Table 2. Strength and weakness of segmentation techniques

Segmentation Techniques	Strength	Weakness
K-means Clustering	Relatively easy and fair fast. K-mean is appropriate for the segmentation of vast numbers of dataset images.	The worse scenarios are bad results.Time consumption. Clusters need to be on the same scale because the closest centre cluster location is the right one.
Histogram matching	The low difficulty of measurement. No prior specifics are needed.	Spatial knowledge is not taken into consideration and does not guarantee the neighbouring segments.
Region-based	Noise in the procedure of	Serious measurement difficulty.

techniques	identification.	Display of square elements in the area due to the partitioning technique.
Edge detection	The study is practical for photographs of more contrast illnesses.	This approach would not work better if the picture has several edges.
Fuzzy techniques	The Inference can be made with fuzzy.	Computation should be focused.
Otsu Thresholding	If two classes, such as the front and background, are performed, Otsu thresholds are suitable.	It takes less time.

3.3.Feature's extraction-based techniques

Feature extraction performs a critical function for the input image identification of an entity in the field of machine learning and computer vision. Each entity has its form, motion, scale, colour, and texture, such that the extracted object is categorized in its relevant class through the extraction of features. The characteristics were built in the frameworks, which assumed the disease component definition based on its form, scale, origin, colour, and texture(Khan et al. 2018). Many extraction strategies, including layout, colour, and texture, are extracted in agriculture, and each type of feature has its challenges. Essentialelements for disease detection based on scale, texture, and colour in fig. 4. However, all colour features are more critical as each colour has its significance(Oo and Htun 2018).

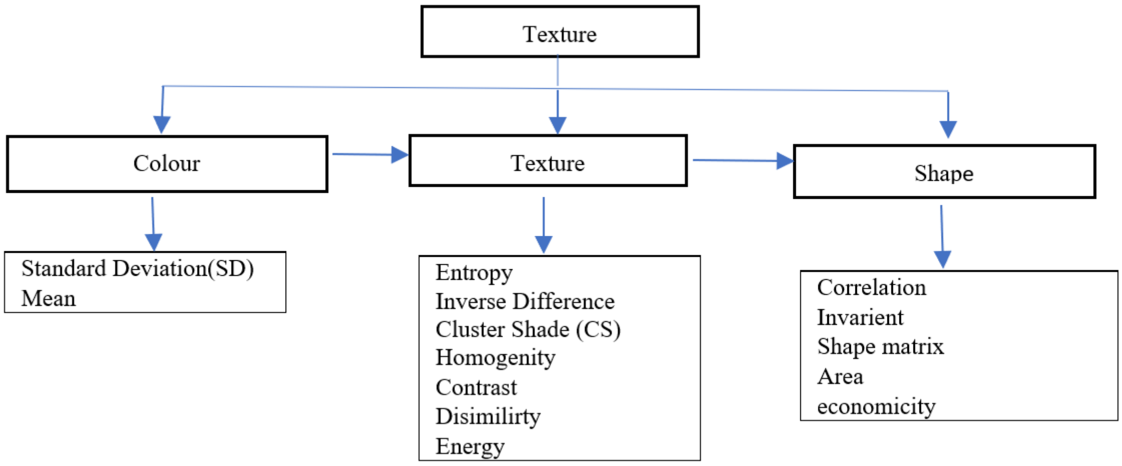

Figure. 4 Features categories

3.3.1. Challenges

Citrus features like colour, shape, and textures are extracted. These disadvantages degrade the accuracy of the system. There are many problems in the feature extraction process:large size of features,high calculation-time, trivial features, redundancy in extracted features, changes in the illumination conditions, no consistent grading and revolution. These problems impact machine functionality directly(Iqbal et al. 2018).

3.3.2. Disease detection by colour features

Colour is an essential function in disease identification. Whenever people experience an image, colour is imperative that they noticed it. Several colour models exist, including Hue, Saturation, and Value(HSV), YCbCr, Red Green Blue (RGB), andHue, Saturation and Intensity(HSI). The HSV prototypical is used to recognize the colours, the saturation being the degree of colour clarity in the pictures and the magnitude being the strength or luminosity(Jhuria, Kumar, and Borse 2013).

3.3.3. Disease detection by texture features

The texture characteristic of regular plants is contrasted with the texture characteristic of the leaves (Lalitha, Muthulakshmi, and Vinothini 2015). Firstly, there are four major components:processing RGB images and then translating these images into an HSV space transition structure. The green picture element is screened and removed using a specific threshold cost for segmented images. In the end, texture characteristics are derived using SGDM(Iqbal et al. 2018).

3.3.4. Disease detection by form features

The form(shape) is the essential characteristic of the picture representation. The correct extraction of the form attribute depends on the method of image segmentation. Since the photographs have been segmented, the border and pixel of regions are surrounded by the boundary. Thus, form characteristics are split into two stages: primary, the region-based attribute, and second limits-based.

3.4. Classification methods

Techniques dependent on classifiers are used to classify the images depending on their extractions. The final phase of the work involves discovering an appropriate leaf disease classification algorithm for the group they belong. We have selected five main classification algorithms to control their classification suitability. The algorithm with the best efficiency is designed to construct a final model for its hyperparameters. Multi-SVM, Artificial Neural Networks (ANN), Random Forest (RF), Naive Bayes(NB), and K-NN are used in this analysis.The comparative accuracy disease classification of different classifiers shown in Table 3.

Multifunctional SVM (Support Vector Machine): The SVM is a monitored knowledge-based algorithm used for sorting, regression, clustering, and detection. SVM is essentially a binary linear classifier that separates two groups with the maximum hyperplane margin. A hyperplane with the longest distance to the closest data points, thus called a maximum margin hyperplane, provides a good separation; the more significant the margin lower the generalization error. The feature set may occur in a finite-dimensional space, but it is not linearly separable in that space. To render the data linearly separable, the kernel function is converted into a higher dimension domain, where it is linearly separable.

The binary grouping essence of SVM is solved by several single-vs-all and one-vs-one strategies. All classes are chosen individually in one-vs-all Multi-SVM. One is considered a good mark, and all other categories are educated as negatives and N classifiers. The issue with imbalanced data is that one class has fewer than all the other types of samples, and general SVM implementation may be improperly conducted. One-vs-one train is a different classification for each level, matched one by one, which overcomes the imbalance issue.This contributes to $X(X-1)/2$ classifiers that make it even more computer-cost.

Artificial neural networks: ANNs are computer algorithms based on bio-artificial neural networks. These systems may execute tasks without explicit rules from labelled instances. They dynamically change the weight of the neurons for a classification task using training examples and attempt to identify new cases based on the trained consequences. The input layer, output layer, and one or more hidden layers of a multi-layer Artificial Neural Network are accessible. The number of neurons in the input layer usually is equivalent to the duration of the functional vector, and the number of neurons in the output layer equal to the number of groups. The number of hidden layers and neurons in each hidden layer varies depending on the specific problem set and cannot be calculated in advance.

Random Forest: Overfitting is the underlying dilemma of a decision tree to overcome various storage methods or praises. Random forest, which fits a series of decision trees on multiple sub-samples of training data sets and uses an average for improved predictive precision, solves the issue of overfitting. The sample size is still the same as the sample size so that the samples are replaced. The main benefit of reducing over-fitting is that random forests are more exact than plain decision trees in most situations. However, the algorithm is complex, and its forecast pace is sluggish. Estimates are founded on maximum probability(Ahmed, Asif, and Saleem 2021).

Naïve Bayes: It is a stochastic classification technique centred on the principle of Bayes that each function is autonomous. It seems incorrect and simplistic to assume that each process is independent of some other feature collection feature. This belief also helps mitigate the complications caused by the dimensionality curse. Nevertheless, in real-world environments, Naïve Bayes needs no training data and can be calculated quickly.

Naïve Bayes is an algorithm, andseveral classification algorithms are built on the general belief that a particular feature is independent of some other feature. It can be effectively learned through a guided learning method, and in specific parameters, estimates the maximum probability.

K-NN: This is a non-parametric algorithm used to detect grouping, regression, or outlier. It is a supervised learning algorithm that does not attempt to build a model but instead stores the data's training examples. The designation is carried out by a clear majority vote of the closest neighbours. This is a favourite algorithm for massive or noisy training data and is simpler to apply. Selection of the value of K is the issue with K-NN. Less importance of K allows more acceptable boundaries of decisions leading to overfitting, and higher K results in cleaner boundaries leading to worse classification accuracy owing to higher bias. The determination of K's adequate value is computationally costly because all training samples must calculate the distance from each case

Table 3. Various classifiers accuracy

Year/Reference	Problem	Methodology	Dataset	accuracy
2016(Sladojevic et al. 2016)	Deep NN a Leafclassification recognition of plant diseases.	Deep CNN	Dataset of citrus photographs obtained from the Internet.	96.3%
2016(Wetterich et al. 2016)	Detecting Citrus canker	SVM	Training samples size-20 Test sample size-180.	97.8%
2016(Sandika et al. 2016)	Detect disease in grapes leaves.	Random forest	Grapes leaves	86%
2016(Waghmare, Kokare, and Dandawate 2016)	Detection of diseases in grape leaves.	SVM classifier	450 leaves image,160 healthy and 290 diseased.	96.6%.
2016(Padol and Yadav 2016)	Detection disease in grape leaves	SVM	Grapes leaves	88.89%
2017(Ustad, Korke, and Bhaldar 2007)	Identification of a diseased region of grape leaves.	SVM	grape leaves	90%.
2018(Behera et al. 2018)	Classify Orange fruits diseases.	M-SVM	The dataset of orange fruit is 20 images	90%
2019(Doh et al. 2019)	Citrus diseases classification.	SVM, ANN	Kaggle dataset images	SVM - 93.12% ANN - 88.96%
2019(Adeel et al. 2019)	Finding optimum grape characteristics from pictures.	Multi-SVM	plant village dataset	91.4%
2019(Aravind et al. 2018)	Extraction of features from the grape leaves.	CNN	The dataset consisted of 4063 diseased leaves.	99.23% .
2019(Jaisakthi et al. 2019)	Detection of diseases in grapes	Adaboost SVM, Random Forest	plant village dataset 5675	Adaboost –74.79% SVM – 91% Random Forest – 83%

3.5. Performance measures

Several success metrics are included in algorithm assessment literature. This has performance, sensitivity,accuracy rate, curve region (AUC),time, FNR, and FPR in Table 4. Exactness distinguishes between right and incorrect samples thatevaluate the true negatives and truepositives. The sensitivity is often defined as an actual positive rate that determines the photographs are appropriately labelled. The AUC is equal to the likelihood that a classifier classifies how far more optimistic or pessimistic is the situation? (Radhakrishnan 2020).

Table 4. Performance measures

Sr. No.	Performance Measure	Formula
1	Mean Square Error (MSE)	$\frac{1}{MN}\sum_{y=1}^{m}\sum_{y=1}^{m}[I(x,y)-I'(x,y)]^2$ Where I(x,y) - Original image I'(x,y) - Decompressed image M,N - Dimensions of the images
2	Peak Signal to Noise Ratio (PSNR)	$20*\log\left({}^{255}/_{\text{sqrt(MSE)}}\right)$
3	Root Mean Square Error (RMSE)	$\sqrt{MSE}$
4	Accuracy	$\frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{FP}+\text{FN}+\text{TN})}$
5	True Positive Rate (TPR)	$\text{TPR}=\frac{\text{TP}}{(\text{FP+TN})}$
6	False Positive Rate (FPR)	$\text{FPR}=\frac{\text{FP}}{(\text{FP+TN})}$
7	False Negative Rate (FNR)	$\text{FNR}=\frac{\text{FN}}{(\text{TP+FN})}$
8	Precision	$\frac{\text{TP}}{(\text{TP}+\text{FP})}$
9	Sensitivity	$\frac{\text{TP}}{(\text{TP}+\text{FN})}$
10	Specificity	$\frac{\text{TN}}{(\text{FP}+\text{TN})}$
11	Recall	$\frac{\text{TP}}{(\text{TP}+\text{FN})}$
12	Area under Curve (AUC)	$\frac{\sum Rank(+)-\mid+\mid X(\mid+\mid\frac{\mid+\mid 1)}{2}}{\mid+\mid+\mid-\mid}$ Where ∑ Rank(+) is the ranks of all positively classified samples |+| is the number of positive examples in the dataset |-| is the number of negative examples in the dataset

4. Discussion

This section addressed the detection and grouping of illnesses in citrus fruits and leaves, their benefits, andtheir drawbacks. Pre-processing techniques show how Euclidian distance techniques, improved colour symbols, and grayscale techniques work well in most citrus diseases. The segmentation process is a crucial phase in identifying areas that have been contaminated. K-means clustering, single and region thresholding are effective and infected area is easily noticeable. These segmentation strategies do well for identifying the Region of Interest (ROI). Various features like shape, colour, texture, etc. extracted by different techniques, but the identification of disease based on texture features provides good results for disease classification. Other features also help for disease identification. For the efficiency of the classification process, the primary feature collection is more essential. For disease classification, Neural Network and Support Vector Machine techniques provide better classification than other classification techniques.

5. Conclusion

In this survey, several image processing approaches for the recognition of plant diseases are addressed. It involves four key stages, including (1) preprocessing; (2) segmentation; (3) feature extraction; and (4) classification. Every step is compared with its methodology, efficiency, strength, and weakness. Through this survey, we found that image preprocessing strategies contribute to growing the precision of segmentation. During this survey, the k-means technique found the most critical segmentation strategy for diseased plants. The most prominent characteristic of the picture is a texture for the depiction of disease, and SVM and NN are using these characteristics. This requires their efforts to incorporate an effective, fast, reliable, and automated system to recognize diseases on uninfluenced citrus leaves. The population includes prospective teachers of Tirunelveli District. The investigators used simple random sampling technique and randomly selected 250 prospective teachers in Tirunelveli District.

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