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Identification of Citrus Fruit Diseases Through Intelligent Computational Approaches: A Review

Review Article

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Abstract

Agriculture plays a significant role in the growth of human civilization. The fruits and vegetables are an important ingredient in the regular diets of the human. They provide high sources of vitamins and minerals that allow us to remain healthy. Citrus is used as a major source of nutrients along with vitamin C worldwide. The Citrus family consists of grapes, grapefruits, orange and lemons. The Plant diseases highly decline the growth of citrus fruits, creating a significant economic loss in agriculture. The identification of the citrus fruits leaves diseases in naked eyes leads to inaccurate results for the control measurements of pesticides. Hence, early diagnosis of diseases in citrus fruit automatically is necessary to increase the productivity. Image processing techniques are generally used to design a diagnosis system for extracting the features from the citrus plant images and identify the types of diseases at the early stage itself. This paper exhibits survey on different image processing techniques and machine learning approaches used to extract and quick examination of various citrus fruits like lemon, orange, and grapes leaves. The issues faced by the computational approaches for analyzing citrus fruits leaves are also given with future directions.

Keywords: Citrus; Grapes; Orange; Diseases; Image Processing; Automatic Identification.

Introduction

The research in the Agriculture sector aims at increasing production and quality of food with less cost and high profit [1]. Fruits have plenty of vitamins and minerals, fibers and other major non-nutrient substances such as plant sterols, flavonoids and antioxidants. Among fruit plants, citrus plants produce fruits with high sources of vitamin C, which is several benefits for human health and is also used as a raw material in many agro-industries [2].

The citrus fruit plants are affected by various diseases such as citrus canker, Melanose, citrus black spot, etc. Citrus canker is an inflammation of the citrus trees and is extremely infectious and causes yellow halo lesions or scabs on the leaves or fruits. Extreme infections can cause leaf damage, damaged fruit, drop of fruit and death. The cancer bacteria readily and rapidly disperse to air currents, plants, birds and also the humans via clothing and infected components [3].

The Melanose citrus disease can damage young leaves and fruits of some citrus varieties as their tissue expands and develops over long periods when the environment is rainy or damp. The signs of this common fungal disease ranges from small patches or scab-like lesions, which are also referred to as tear drop, mudcake or star melanoses [4].

Citrus black spot (CBS) disease is caused by Phyllostictacitricarpa fungus and affects citrus plants in tropical climates, decreasing the quantity and quality of the fruit. Early CBS infections tend to be thin, oval, slightly elevated, reddish-brown with light centers and also a diffuse yellow halo. The older lesions are decayed with a dark brown border and a grey center [5]. Anthracnose is caused by the Colletotrichumgloeosporioides fungus, which occurs in the canopy on dead wood, and it extends short distances by rain splash, strong dew and overhead irrigation [6]. Table 1 presents the symptoms and favorable conditions of various Citrus diseases.

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Table 1. Symptoms of various citrus plant diseases.

Citrus Disease Name	Symptoms	Favorable conditions
Citrus Scab	Tiny, semi-translucent, lesion-like dots form on leaves.	Summer period
Citrus canker	water-soaked margin with yellow halo.	Spring season
Citrus tristeza disease	In early stages, the disease affected in tree leaves is chlorotic. The leaves slowly drop and the defoliated twigs drop dead-back	warm summer conditions
Gummosis	Disease starts as water saturated large patches on the stem's basal portions near ground level.	moist and cool conditions.
Powdery mildew	On the top of the leaves exist	relative humidity (RH) and spread through wind
	thin patches of white or gray powdery masses.	
Anthracnose	lesions with brown to black spots	Cool weather
Sooty mould	blackening of the leaves.	summer
Powdery mildew	White powdery spores often grow on the upper surface.	Cool and damp weather
Downy mildew	Infected leaves produce light yellow-green lesions, slowly becoming brown. Infected leaves also falls prematurely.	wet spring and a warm summer
Alternaria blight	dark brown-purplish blotchesvisible on leaves.	Warm weather and moist conditions.
Black rot	reddish brown marks irregularly developed on the leaves	Warm weather and moist conditions

The computational approaches play a major role in automatic identification and early diagnosis diseases in citrus fruits for increasing growth and quality. Image processing techniques such as preprocessing, image segmentation, features extraction and classification are used to design a diagnosis system to identify the diseases in citrus plants. Typically, the users used sensors and cameras to acquire the Citrus leaves and fruit images from the field. The preprocessing techniques remove noises from the captured images and enhance the images. Image segmentation techniques are used to identify the diseased region and also detects the boundary regions of disease affected spots. The feature extraction techniques extract the features from the diseased regions. Finally, the classification techniques are applied to recognize the citrus plant diseases.

In this study, systematic reviews on computational approaches for efficient diagnoses of diseases in citrus fruit have been conducted. The rest of the paper is organized as follows: Review of literature with the issues behind the diagnosis of citrus leaves diseases is exposed in computational approaches for diagnosis of citrus fruit diseases Section. The performance metrics used by the various researchers for citrus plant diseases diagnosis is exposed in performance measures section. Finally, the paper is concluded with further directions.

Computational Approaches for Diagnosis of Citrus Fruit Diseases

Computer-assisted plant disease detection is an important research topic. Since, it is beneficial to detect diseases from symptoms appearing on leaves at an early stage. The electronic databases such as IEEE Xplore, Scopus, Science Direct, Springer Link, Wiley and Google Scholar have been extensively searched for potential studies of various computational models used in Citrus fruits disease detection from 2007 to 2020. The reliable online articles such as thesis and book chapters were also searched for literature surveys. The depth review of computational approaches for diagnosis of Citrus leaves diseases are presented in the following section. The general structure so far applied for identification of citrus plant diseases and also the methods adopted by various researchers for each stage of the plant diseases detection is exposed in Figure 1 and the same is discussed here under.

Computational Approaches inCitrus Plant Diseases Diagnosis: A Review

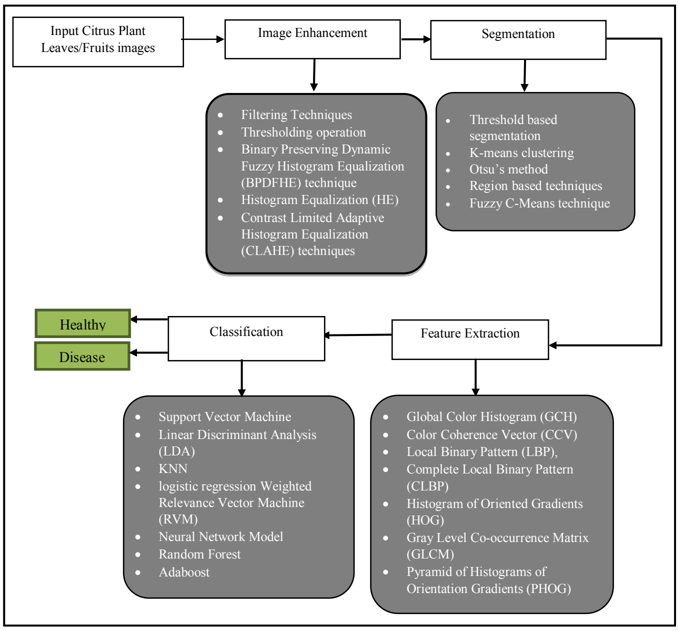
In 2006, J. Blasco et al., [7] proposed Region Oriented Segmentation method for identification of citrus fruit peel defects. The dataset consists of 279 mandarins and 356 Oranges, in which 2132 individual surface blemishes and 162 stems were visible from the fruits. The average detection rate of defects from the tested image is 94.2%.

In 2007, R. Pydipati et al., [8] constructed Colour Co-occurrence Matrix for citrus fruit and extracted feature set with 4 data models such as 1B, 2B, 3B and 4B. The classifiers such as Squared Mahalanobis Distance, Back-Propagation Algorithm, and Neural Network with Radial Basis Functions were evaluated over the 4 data models. All the methods yielded only the best classification accuracy for the Model 4b feature set and their earned classification accuracy was 85%, 98.75% and 97.5% respectively.

In 2007, J. Blasco et al., [9] proposed a multispectral algorithm to detect defects in citrus fruit. Three types of image analysis such as Fluorescence (FL), Ultraviolet (UV) and Near Infrared Image (NIR) analysis were combined to detect defects. Linear Discriminant analysis was adopted for classification. The model achieved the maximum classification accuracy of 87.2% for HIS color space. The combined spectral analysis showed superior performance in identifying defects Compared to the individual analysis of FL, UV and NIR.

In 2007, J. Blasco et al., [10] developed combined multispectral and morphological features to identify defects in Citrus fruit. For 86% of the cases, the proposed system successfully identified the defects. Using only visible information, 82% of defects were cor-

Figure 1. Stages of Citrus Plant Diseases Identification.



rectly identified whereas the confusion matrix arises only between serious and slight defects. The green pattern can be detected with Ultra Violet Fluorescence (UVFL) for 97% of cases and anthracnose can be detected by NIR in 95% of cases.

In 2008, Meunkaewjinda et al., [11] developed a hybrid intelligent system to identify grape leaf diseases. A self-organizing Map (SOM) with Neural Network is applied to recognize the colors of grape. Segmentation is performed using Self organizing Map with a Genetic algorithm. Color features were extracted using Gabor filters. Finally, SVM classifies extracted features into diseases such as rust, scab, and normal. The dataset consists of 489 rust, 497 scab and 492 disease free grape leaves. The disease detection accuracy of the proposed method was 97.8%.

In 2009, G. Kim et al., [12] introduced Stepwise Discriminant technique for the classification of citrus disease. The feature was extracted using Color Co-Occurrence (CCM) matrix. The three classification models such as all leaf conditions, all leaf conditions except young flush leaves and all leaf conditions except young flush and mootle yielded the classification accuracy of 86.67%, 95.50% and 97.33% respectively.

In 2009, Kim et al., [13] extracted color and texture features to identify diseases in grapefruit peel. A colour imaging system was built to obtain RGB images from healthy grapefruits and five common diseased peels including canker, melanosa, greasy spot, wind scar and copper burn. GLCM extracted 39 texture features for each sample fruit images in the HSV space. The stepwise discriminant analysis was used to select the relevant features for the classification models. The dataset consists of 30 samples in which 20 samples used for training and 10 samples for testing. Four models such as HIS_13, HS_9 and I_11 and HIS_39 were developed for classification using the selected texture feature sets of the three color combinations [(H, S, I), (H, S), and (I)]. HSI_13 consists of 13 texture features. Nine and 11 texture features were in HS_9 and model I_11. HIS_39 consists of all 39 texture features. He overall classification accuracy of HIS_13, HS_9 and I_11 and HIS_39 models were 96.7%, 86.7%, 81.7% and 88.3% respectively.

In 2010, Garcia et al., [14] introduced a Multivariant image analysis approach to identify defects in Citrus fruit. In the proposed method, Principal Component Analysis is used to extract reference Eigenspace from matrix which is constructed by unfolding color and spatial data of defect-free peel samples. The dataset consists of 120 samples of oranges and mandarins. The success rate for detecting individual defects was 91.5%, whereas for the damaged samples the proposed method yielded 94.2%.

In 2011, Lorente et al., [15] introduced Multilayer Perceptron (MLP) with an Extreme Learning Machine for decay detection in citrus fruit. The proposed classifier identified two classes such as decay and not-decay. The decay class consists of two infections such as P.digitatum and P.italicum. The classes such as green sound skin, orange sound skin, and scars were grouped into not-decay. Three features approaches were chosen for classification based on spectral index values. The achieved highest success rate of ELM was 95.5%.

In 2011, Zhang et al., [16] projected a two-level hierarchical detection structure to identify canker lesions. The dataset consists of 1000 positive and 2000 negative samples. The proposed zone-based feature extraction was compared to image based feature set. The performance of four classifiers such as Adaboost, Radial Basis Network, KNN and SVM were evaluated. The result showed that Adaboost achieved better performance compared to others. And also the experimental analysis revealed that zone based feature set yielded the highest classification rate of 88%.

In 2012, D. Lorente et al., [17] applied the area under the ROC curve to select features of citrus fruit from the hyperspectral images to identify defects in Citrus fruit. The performance of the ROC feature selection method was compared to three constructed feature selection approaches such as I, II and III. The number of features chosen by the approaches I, II and III were 6, 7 and 4 respectively. The ROC feature selection method yielded highest detection rate of 95.52% compared to Feature selection approach III.

In 2013, Bandi et al., [18] analyzed four classifiers such as Naïve Bayes classifier (NBC), k Nearest Neighbor (KNN), Linear Discriminant Classifier (LDA) and Random Forest Tree (RFT) algorithms in the identification of diseased citrus leaves. The dataset consists of 40 samples. Features were extracted through the Gray Level Co-occurrence Matrix (GLCM). The classification accuracy of KNN, NBC, LDA and RFT were 77.5%, 95%, 98.75%, and 97.5% respectively.

In 2013, Stegmayer et al., [19] tested three classifiers such as CART, Naive Bayes, and Multilayer Perceptron (MLP) classification models in the recognition of citrus diseases. Two datasets with 90 features and 14 features were used to measure the classification performance. The performance MLP is best in classifying diseases such as citrus canker, black spot, and scab. MLP achieved a classification ratio of 83% for all classes of quarantine/not-quarantine samples. In 2013, S.Sannakki et al., [20] applied Feed Forward Neural Network to identify grape leaf diseases. The thresholding technique masked green pixels and anisotropic diffusion filter removed noise from the images. The diseased portion from segmented from grape leaf image using K-means clustering. The dataset consists of 16 powdery Mildew and 17 downy mildew images. The training accuracy of Feed Forward Neural Network was 100%.

In 2013, S. Sannakki et al., [21] proposed Feed Forward Neural Network and k-Nearest Neighbor (kNN) for weather forecasts which utilized moisture and temperature as parameters to predict disease outbreaks in grapes. The system is designed with two modules such as weather forecasting and disease prediction. This weather data is taken from Belgaum/Sambra at the latitude of 15.85, longitude of 74.61 and altitude of 758.

In 2013, M. Bulanon et al., [22] applied Linear Discriminant Analysis and Artificial Neural Networks to identify black spots in citrus fruit through hyperspectral image analysis. The citrus fruit images were only selected from the four optimal wavelengths such as 493nm, 713 nm, 629nm and 781 nm for classification. LDC and ANN achieved an overall classification accuracy of 92%.

The method established in 2013 byPranjaliVinayakKeskar et al., [23] consists of four stages for the identification and diagnosis of leaf diseases. HSI transformation, histogram analysis and intensity adjustment are performed to enhance the image. The segmentation is carried out by the fuzzy algorithm. The color, size and shape features of the diseased spots are extracted and classified using Artificial Neural Network. The whole system is treated as three components such as image analyser, feature repository and classifier. The system works in two phases such as Offline and Online. In the offline phase, a large set of defected input images was processed by image analyser for extracting abnormal features. These features were stored in the classifier's function repository for subsequent usage. During the online process, the pathological feature retrieved by the image analyser from a single defective image is placed into the classifier to identify the specific disorder. In 2014, Narvekar et al., [24] constructed Spatial Gray-level Dependence Matrices [SGDM] from grape leaves images to extract features for the identification of various diseases. About 100 plant leaves of different native plant species in Maharashtra have been collected for analysis. The leaf images acquired are translated to HSI format.Otsu thresholding technique identifies the diseased regions. The co-occurrence features including, Cluster shade and Cluster prominence for classification were extracted from its hue content.

In 2014, R. Gavhale et al. [25] adopted the Support Vector Machine (SVM) to classify citrus leaf diseases. The training dataset consists of 200 images of Citrus canker and Anthracnose diseased leaves. The testing set consists of 50 images. The Genuine Acceptance Rate (GAR) of SVM with RBF and SVM with Polynomial kernel was 96% and 95% respectively.

Artificial Neural Network (ANN) is used to identify grape leaf diseases by Nivedita.R.Kakad et al., [26] in 2015. Canny edge detection method segment the diseased region where features were extracted through GLCM and the same were given as an input to ANN. The ANN is trained with 115 images of different disease type and 40 images were used for testing. The classification rate of ANN was 92.94%.

In 2015,R.Kakade et al., [27] adapted SVM to classify diseases in grape leaves. Initially, the RGB image was converted into HIS space. Split and merge segmentation technique is used for segmentation of RoIs. Spatial Gray-level Dependency Matrices (SGDM matrix) is constructed for each RoIs to extract the features. Finally, SVM identified the diseases in grape leaves using extracted features.

2015, Priyaet al., [28] developed a knowledge-based system to identify plant diseases in lemon leaves. In the proposed approach, gray level threshold segmentation used to convert the grayscale images into binary images. Then the canny edge detection method extracted the features in segmented image calculated threshold value using a histogram. The threshold value of normal leaf always in the range of 30-32 where infected leaf lies out of the range. In the classifiers, the disease name was stored with the threshold value and remedy. If it's infected, then the alarm will be generated to intimate the owner about the disease outbreak.

In 2016, K.Padmavathi et al., [29] applied region merging and patching concept to segment the diseased region in citrus leaves. The performance of the proposed method was compared over Lazy Random Walk (LRW) method. The evaluation metrics such as Achievable Segmentation Accuracy, Boundary recall and under segmentation Error were calculated. The proposed method yielded an accuracy of 75%, whereas LRW achieved only 72%.

In 2016, Kamlapurkar [30] proposed an image processing techniques to identify and classify the diseases in leaf images accurately. The steps in the process are Preprocessing and Identification of Powdery Mildew, Downey Mildew diseases. Using the discontinuity and similarity principles the diseased region is extracted from the grapes leaves.

In 2016, Baldomero et al., [31] applied KNN techniques to detect Potassium Deficiency in grapes leaves. The segmentation method K-Nearest Neighbors (KNN) was compared to the histogram technique. The proposed method was tested using 25 images of healthy and affected leaves. Six varieties of red grapes such as Cabernet Sauvignon, Cabernet Franc, Merlot, Malbec, Shiraz and Tempranillo used to assess the methods. The 25 images healthy and affected leaves divided in two groups for classifications. Histogram based methods work with grayscale intensity images and can't distinguish between colors. The proposed method can be adapted to detect one or many nutritional deficiencies and classify the symptoms.

In 2016, Sladojevic et al., [32] proposed Deep Convolutional Networks as an approach to recognize 13 types of plant diseases. The dataset consisted of 30880 images and 2589 images for training and testing respectively. The average precision of the CNN to recognize the pathogens was 96.3 percent.

In 2016, Petrellis [33] proposed Windows Phone application for measuring the plant lesion features for reliable diagnosis using descriptive information provided by the user. Appropriate actions can be suggested to the user based on these measurements. The most important symptoms of the disease include lesions, overdevelopment, or underdevelopment of various parts of a plant, necrosis and deteriorated appearance. The color, area and number of the lesions can often be used to determine the disease that has mortified a plant. The spots on citrus tree leaves (orange and tangerine), as well as pear trees have been used as case studies. In order to evaluate the developed spot recognition, algorithm 20 tangerine and 20 pear tree leaves images were used. The proposed system recognized 90% of lesions.

In 2016, Wetterich et al., [34] applied the SVM and Fluorescence imaging system to identify Citrus canker and Huanglongbing (HLB) detection. The classification accuracy of the method to identify citrus canker and citrus scab was 97.8% whereas 95% of accuracy was earned in identifying HLB and zinc deficiency.

In 2016, K. Padmavathi et al., [35] dedicated Recursively Separated Weighted Histogram Equalization (RSWHE) technique to enhance the contrast of Citrus leaf images to identify citrus canker diseases. In the second stage, the median filter is applied to remove the unwanted noise from the citrus images. The proposed approaches increase the quality of the images which can be utilized for further processing.

In 2016, M. Abdelsalam et al., [36] devoted a voting technique to identify defects in citrus fruit. Initially, the orange fruit is segmented from the NIR and RGB images. Thresholding method identified defects in seven different color components. Finally, the voting process classifies the defects. The dataset consists of 43 defect-free and 100 defected orange fruits. The overall accuracy of the algorithm was more than 95%.

In 2016, Sandika et al. [37] applied the Random forest technique to identify grapes leaves diseases. The performance of Random Forest is compared with PNN, BPNN and SVM. The feature extraction algorithms such as Local Binary Pattern (LBP), GLCM features and local texture features were used. The experimental result proved that the Random forest with GLCM features yielded the highest classification accuracy of 86%.

In 2016, Waghmare et al., [38] introduced the SVM classifier to identify the diseases in grape leaves. The dataset consists of 450 grape leaves, in which 160 healthy leaves and 290 diseased leaves. SVM yielded a classification accuracy of 96.6%.

In 2016, K. Kharde et al., [39] applied the Neural Network technique to identify grape leaf diseases. Otsu algorithm and watershed segmentation techniques were applied for segmentation. The proposed method yielded an overall classification accuracy of 93.44%.

In 2016,K. Kharde et al., [40] applied ANN to identify 3 types of diseases such as Downy mildew, Powdery mildew and Black rot in grape leaves. The grapevine images were captured using mobile and stored in the Raspberry Pi system. Finally, image processing techniques were applied to identify the types of diseases. ANN yielded an overall classification accuracy of 93.33%.

In 2016, B. Padol et al., [41] applied SVM to identify grape leaf diseases. The diseased region is segmented using K Means clustering. Color and texture features were extracted from the segmented images. SVM yielded an accuracy of 88.89% to identify the grape leaf diseases.

In 2017, Tete et al., [42] applied Thresholding and K- means cluster algorithms to detect different plant leaf diseases. The digital images of plant leaves are acquired from the field using a camera. The image is preprocessed and segmented the original image to identify the infected parts of the plant leaf. The various varieties of plant leaves such as guldaudi leaf, lemon leaf, rose leaf and bitter gourd leaves with specific diseases were examined. The k means clustering recognized the diseased region and the results were expressed qualitatively.

In 2017, H. Ali et al., [43] proposed ΔE color difference algorithm to segment the diseased region in citrus fruit. Dataset includes 199 images with 99 infected with disease and 100 healthy images of citrus plants. Color and texture features were extracted from the segmented image. The classification techniques such as KNN, Cubic SVM, Boosted and Bagged tree classifiers were used to identify the types of diseases. The experimental result showed that the Bagged tree classifier outperformed others. The Bagged tree ensemble method achieved an accuracy of 99.5%, 100%, and 100% for disease level in RGB, HSV and LBP features respectively.

In 2017, K. Hase et al., [44] used the Fast Library for Approximate Nearest Neighborhood (FLANN) technique to identify diseases in tomato and grape leaves. The proposed system was developed in the Android environment. The diseased region is extracted using the adaptive thresholding technique. FLANN identified Bacteria and Fungus diseases in tomato and grape leaves. The proposed method achieved an accuracy of 91.5% and 94% in identifying Bacteria and Fungus diseases in tomato leaves. Similarly, the accuracy of identifying bacteria and fungus disease in Grape leaves was 93.2% and 94.7% respectively.

In 2017, S. Ustad et al., [45] applied K means clustering to extract the diseased region of grape leaves. Various features such as color, texture and shape were extracted from the segmented images. Then, SVM identifies the types of diseases in grape leaves. The average classification accuracy of SVM was 90%.

In 2018, Sharif et al., [46] dedicated optimized weighted segmentation method to detect lesion spots in citrus fruits. The color, geometric and texture features were extracted and the features set were reduced using PCA. The extracted features were given as input to the multi-SVM to classify the diseases. The proposed method was tested over 1000 citrus fruits images with various diseases such as canker, anthracnose. The performance of the optimized weighted method was compared to W-KNN, LDA, DT and Ensemble Boosted Tree (EBT) methods. The classification accuracy of optimized segmentation method achieved 96.9% which was superior to others.

In 2018, Banni et al., [47] devoted the Bi-Level Thresholding technique to segment the diseased region in citrus leaves. The various citrus leaves images collected from the plants like grapefruit, lemon, and orange. The features were extracted using the GLCM technique and the framed Hidden Markov Model is applied to classify the diseases. The dataset consists of 236 samples of citrus diseased leaves. The accuracy of the method to identify canker, Anthracnose, overwatering and citrus greening was 85.71%, 84.21%, 82.50% and 78% respectively.

In 2018, Behera et al., [48] personalized Multiclass SVM to classify the diseases in Orange fruit. The K-means clustering used to segment the diseased region where features were extracted using the GLCM technique. The severity of the disease is measured using Fuzzy logic. The dataset consisted of 20 diseased orange fruit. The proposed method yielded an accuracy of 90% to identify canker, Melanose, stubborn disease, brown rot diseases and healthy fruits.

In 2019, I. Ojelabi et al., [49] applied the K-means clustering technique to extract the diseased region in citrus fruit image where the color, geometric and texture features were extracted and the same was reduced using PCA. The extracted features were given to SVM to classify the diseases. The dataset consisted of 190 diseased citrus fruit samples. The performance of the proposed method was compared with the KNN classifier. The SVM classifier yielded an accuracy of 95% which is 6% higher than KNN.

ANN and SVM classifiers used to classify citrus fruit diseases by Doh et al., [50] in 2019. The K-means clustering technique extracted the diseased region from the leaves images. The average classification accuracy of ANN and SVM was 88.96% and 93.12% respectively.

In 2019, Patel et al., [51] dedicated the K-Means clustering technique to segment the diseased spot in pre-processed orange fruit images using a median filter. The color, texture and shape features were extracted from the diseased region and classify the same with the SVM classifier. The combination of Color Moment, shape and GLCM features yielded the highest accuracy of 67.74%.

In 2019, Andrushia et al., [52] adapted the Artificial Bee colony optimization technique to find the optimal features from the constructed feature sets of grape leaves. The cellular automation filter removed the noises from the image. The color, shape, and texture features were extracted from the grape leaves. The extracted features set given as input to the ABC algorithm to find the optimal features set. Then, the SVM classifier classified the diseases. The plant village dataset is used for experimentation. The performance of SVM was compared to the KNN classifier. The performance of the ABC feature selection method was compared with PSO and Genetic algorithm. The experimental results showed that SVM with ABC feature selection yielded 93.01% of accuracy, which was superior to other methods.

In 2019, Miaomiao Ji et al., [53] proposed CNN with united Model to identify grapes leaves diseases. The united Model hybrid the features of ResNet 50 architecture and Inception V3 component to extract the features of grapes leave images. The dataset collected from the plant village. The performance of CNN with unitedModel was compared with various CNN architectures such as ResNet, GoogleNet, DenseNet VGGNet. The testing accuracy of United models was 98.57%, whereas GoogleNet, ResNet, VGGNet and DenseNet yielded an accuracy of 95.47%, 98.09%, 93.32% and 96.62% respectively.

In 2019, Adeel et al., [54] proposed a Canonical Correlation Analysis (CCA) approach to find the optimal features from the grapes leaves images and multi SVM is adapted for classification. In the pre-processing stage, Local Contrast Haze Reduction (LCHR) is used to enhance the contrast of the diseased region. The color, geometric and texture features were extracted, which are used by CCA to find the optimal feature set. The proposed method was tested over the plant village dataset. The performance of M-SVM is compared with Ensemble Subspace Discriminative (ESD), Quadratic SVM (QSVM), Linear Support Vector Machine (LSVM), Cosine KNN(CKNN) and Cubic K-Nearest Neighbor (CKNN). The accuracy of M-SVM was 91.4%, which is superior to others.

In 2019, K. R. Aravind et al., [55] applied CNN with Alexnet with a transfer learning approach to extract features from the grape leaves. The dataset consisted of 4063 diseased leaves. The proposed CNN with Alexnet architecture utilized 7 rectified linear unit (ReLu), 5 Convolution layers, 3 normalization layers, 2 drop out layers, and one softmax layers to extract the features. The extracted features were applied to Multi-SVM to classify the diseases. The proposed method yielded an accuracy of 99.23%.

In 2019, S.M. Jaisakthi et al., [56] devoted the methods SVM, Adaboost and Random Forest to identify grape leaves diseases. The background of the grape leaves images were removed using a graph cut method. The global thresholding technique used to extract the diseased region from the grape leaves. The GLCM technique personalized to extract the features. The dataset consisted of 5675 grape leaves images collected from the plant village dataset. The experimental result proved that the classification accuracy of SVM, Random Forest and Adaboost techniques were 91%, 74.79% and 83% respectively.

In 2020, Singh et al., [57] applied Support Vector Machine, Linear Discriminant Analysis, K-Nearest Neighbours and Multi-Layer Perceptron technique to classify the citrus leaf diseases. The k-means clustering technique segmented the diseased regions in leaves where the color and texture features were extracted. The ANOVA F-test is applied to select the important features. Finally, the above classification techniques were applied to identify the diseases. The dataset consisted of 236 citrus diseased leaves. The combination of color and texture features set yielded higher accuracy. The accuracy of LDA, MLP, KNN and SVM for color and texture features yielded an accuracy of 84.32%, 81.36%, 77.12% and 80.93% respectively.

The review of various methods used to identify citrus plant diseases is projected in Table1 with their outcome and performance metrics.

Table 2. The review of various methods used to detect Citrus Disease Detection.

Year	Author	Problem	Methodology	Dataset	Parameter
2006	J. Blasco et al.[7]	Identification of peel defects in citrus fruit	Region oriented segmentation	279 mandarins and 356 Oranges, in which 2132 individual surface blemishes and 162 stems were visible from the fruits	The average detection rate - 94.2%.
2007	R. Pydipati et al. [8]	Extraction of features from citrus fruit.	Color Co-occurrence Matrix	Citrus fruit samples	Classification Accuracy Mahalanobis – 85% Back propagation – 87.75% NN with radial basis functions – 97.5%
2007	J. Blasco et al. [9]	Detection of defects in citrus fruit.	Linear Discriminant analysis	Citrus fruit images	Maximum classification accuracy-87.2%.
2007	J. Blasco et al. [10]	Identification of defects in Citrus fruit.	combined multispectral and morphological features	428 defects in oranges and 369 defects in mandarins	Fluorescence image analysis Success rate – 63.4% Ultraviolet image analysis Success rate – 79.5% near-infrared image analysis Success rate – 92.9%
2008	Meunkaewjinda et al. [11]	Identification of grape leaf diseases.	hybrid intelligent system	The dataset consists of 489 rust, 497 scab and 492 disease free grape leaves.	Disease detection accuracy - 97.8%.
2009	Dae G. Kim et al. [12]	Classification of citrus fruit disease.	Stepwise Discriminant analysis	420 Citrus leaves samples with diseases	Accuracy HSI_18 model – 86.67 HSI_15 Model – 95.60 HSI_14 Model - 97.33
2009	DaeGwan Kim et al. [13]	Identification of diseases in grape fruit peel	Stepwise Discriminant analysis	20 citrus fruit samples for training and 10 samples for testing	Average classification accuracy – 96%
2010	Fernando Lopez Garcia et al. [14]	Identification of defects in Citrus fruit	Multivariant image analysis approach	The dataset consists of 120 samples of oranges and mandarins.	Success rate Individual defects - 91.5%, Damaged samples - 94.2%
2011	Lorente et al. [15]	Decay detection in citrus fruit.	Multilayer Perceptron (MLP) trained with Extreme Learning Machine	240 citrus fruit	An average success rate - 87.5%
2011	Zhang et al. [16]	Detection of canker disease in citrus fruit.	Adaboost algorithm	Training set with 3000 samples of citrus canker and testing set with 400 samples	Classification rate - 88%
2012	D. Lorente et al. [17]	Identification of defects in Citrus fruit.	The ROC feature selection method	240 mandarins fruit samples	The highest detection rate - 95.52%.
2013	Bandi et al. [18]	Identification of diseased citrus leaves	Naïve Bayes classifier (NBC), k Nearest Neighbour (KNN), Linear Discriminant Classifier (LDA) and Random Forest Tree (RFT) algorithms	The dataset consists of 40 samples	The classification accuracy KNN - 77.5% NBC - 95% LDA - 98.75% RFT - 97.5%
2013	Stegmayer et al. [19]	To recognize citrus diseases	CART, Navie Bayes and Multilayer Perceptron (MLP) classification models.	212 Nova mandarins samples with the diseases canker, scab, black spot	Average classification accuracy MLP - 86.12% NB - 84.05% CART – 74.28%
2013	S Sannakki et al. [20]	Identification of grape leaf diseases	Feed Forward Neural Network	The dataset consists of 16 powdery Mildew and 17 downy mildew images	Training accuracy – 100%
2013	S. Sannakki et al. [21]	To forecast diseases in grape leaves through weather data	Feed Forward Neural Network and k-Nearest Neighbor (NN)	The weather data is taken from Belgaum/Sambra at latitude of 15.85, longitude of 74.61 and altitude of 758	-
2013	M. Bulanon et al. [22]	Identification of black spot in citrus fruit through hyperspectral image analysis	LDC and ANN	200 orange samples	Average Accuracy LDC – 92% KNN – 92%
2013	Keskar et al. [23]	Leaf Disease Detection and Diagnosis	An image processing system for leaf disease detection and diagnosis.	-	-
2014	Narvekar et al. [24]	Identification of various diseases in grape leaves	Spatial Gray-level Dependence Matrices	100 plant leaves of different native plant species of Maharashtra have been collected for analysis.	-

2014	Gavhale et al. [25].	Classification of citrus leaf diseases.	Support Vector Machine (SVM)	The training dataset consists of 200 images of Citrus canker and Anthracnose diseased leaves. Testing set consists of 50 images	Genuine Acceptance Rate (GAR) SVM with RBF – 96% SVM with Polynomial kernel - 95%
2015	Kakad et al. [26]	Identification of grape leaf diseases.	Artificial Neural Network (ANN)	115 images for training and 40 images were used for testing.	The classification rate - 92.94%.
2015	R.Kakade et al. [27]	Classification of diseases in grape leaves	SVM	Grape leaves images	Qualitatively measured
2015	Priya et al., [28]	Leaf Disease Detection and Classification	Knowledge Based System to Identify plant diseases	Lemon Leaf Diseases	Qualitatively measured
2016	K.Padmavathi et al. [29]	Segmentation of the diseased region in citrus leaves	Region merging and patching concept	Citrus canker diseased leaves	Accuracy Proposed method – 75% LRW – 72%
2016	Kamlapurkar [30]	Identification of diseases in leaves images	Image processing techniques	Grape leaves	Qualitatively measured
2016	Baldomero et al. [31]	Detection of Potassium Deficiency in grapes leaves.	KNN	The 25 images of healthy and affected leaves	Qualitatively measured
2016	Sladojevic et al., [32]	Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification	Deep Convolutional Networks	All the citrus images collected for the dataset were downloaded from the Internet,	The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average 96.3%.
2016	Petrellis [33]	Plant Lesion Characterization for Disease Recognition	Image processing Techniques	20 tangerine and 20 pear tree leaves	Accuracy - 90%
2016	Wetterich et al. [34]	Identification of Citrus canker and Huanglongbing (HLB) detection	SVM and Florescence imaging system	20 training samples and 180 test samples	Accuracy Citrus canker - 97.8% Citrus Scab - 95%
2016	K. Padmavathi et al. [35]	To enhance the contrast of Citrus leaf images	Recursively Separated Weighted Histogram Equalization (RSWHE) technique	Citrus leaves images	Qualitatively measured
2016	M. Abdelsalam et al. [36]	Identification of defects in citrus fruit.	voting technique	The dataset consists of 43 defect free and 100 defected orange fruits.	The overall accuracy of the algorithm was more than 95%.
2016	Sandika et al. [37]	Identification of grapes leaves diseases.	Random forest technique	Grapes leaves	Classification accuracy – 86%
2016	Waghmare et al. [38]	Identification of diseases in grape leaves.	SVM classifier	The dataset consists of 450 grape leaves, in which 160 healthy leaves and 290 diseased leaves.	Accuracy - 96.6%.
2016	K. Kharde et al. [39]	Identification of grape leaf diseases.	Neural Network technique	Grapes leaves	Overall classification accuracy -93.44%.
2016	K. Kharde et al. [40]	Identification of 3 types of diseases such as Downy mildew, Powdery mildew and Black rot in grape leaves	Neural Network technique	Grapes leaves	Overall classification accuracy -93.33%
2016	B. Padol et al. [41]	Identification of grape leaf diseases	SVM	Grapes leaves	Accuracy - 88.89%
2017	Tete et al. [42]	Detection of Plant Disease Using Threshold, K- Mean Cluster and ANN Algorithm	Thresholding and K- means cluster algorithms to detect different diseases in plant leaf.	Plant leaves such as guldaudi leaf, lemon leaf, rose leaf and bitter gourd leaves	Qualitatively measured
2017	H. Ali et al. [43]	Detection of Plant Disease	Bagged Tree classifier	Dataset contains 199 images including 99 are disease infected and 100 are normal citrus plant images	Accuracy – 99.9%
2017	K. Hase et al. [44]	Identification of diseases in tomato and grape leaves.	Fast Library for Approximate Nearest Neighborhood (FLANN) technique	Tomato and grape leaves	Average Accuracy Tomato leaves – 92.75% Grapes Leaves – 93.95%
2017	S. Ustad et al. [45]	Identification of diseased region of grape leaves.	SVM	grape leaves	Accuracy - 90%.
2018	Sharif et al. [46]	Lesion spots in identification in citrus fruits	optimized weighted segmentation method	1000 citrus fruits images with various diseases such as canker, anthracnose	Classification Accuracy - 96.9%

2018	Banni et al. [47]	Segmentation of the diseased region in citrus leaves.	bi-level thresholding technique	236 samples of citrus diseased leaves	Accuracy Canker – 85.71% Anthracnose – 84.21% Overwatering – 82.50% Citrus greening – 78%
2018	Behera et al. [48]	Classification of the diseases in Orange fruit.	Multiclass SVM	The dataset consisted of 20 diseased orange fruit	Accuracy – 90%
2019	I. Ojelabi et al. [49]	Extraction of the diseased region in citrus fruit	K-means clustering technique	The dataset consisted of 190 diseased citrus fruit samples	Accuracy SVM – 95% KNN – 89%
2019	Doh et al. [50]	Classification of citrus fruit diseases.	ANN and SVM classifiers	Citrus fruit images from kaggle dataset	Accuracy ANN - 88.96% SVM - 93.12%
2019	Patel et al. [51]	Identification of the diseased spot in orange fruit.	SVM	Orange fruit images	Accuracy ColorMoment + shape + GLCM features – 67.74%
2019	Andrushia et al. [52]	Finding the optimal features in grape leaves	SVM with Artificial Bee colony optimization technique	Grape leaves from plantvillage dataset	Accuracy - 93.01%
2019	Miaomiao Ji et al. [53]	Identification of grapes leaves diseases.	CNN with unitedModel	The dataset collected from plantvillage	Testing Accuracy - 98.57%,
2019	Adeel et al. [54]	Finding the optimal features from the grapes leaves images.	M-SVM	plantvillage dataset	Accuracy – 91.4%
2019	K. R. Aravind et al. [55]	Extraction of features from the grape leaves.	CNN with Alexnet with transfer learning approach	The dataset consisted of 4063 diseased leaves.	Accuracy - 99.23%.
2019	S.M. Jaisakthi et al. [56]	Identification of grape leaves diseases.	SVM, Adaboost and Random Forest techniques	The dataset consisted of 5675 grape leaves images collected from plantvillage dataset.	Accuracy SVM – 91% Adaboost –74.79% Random Forest – 83%
2020	Singh et al. [57]	Classification of the citrus leaf diseases.	Support Vector Machine, Linear Discriminant Analysis, K-Nearest Neighbors and Multi-Layer Perceptron techniques	236 citrus diseased leaves	LDA - 84.32%, MLP – 81.36%, KNN - 77.12% SVM - 80.93%

Issues Related to Diagnosis of Citrus Leaves and Fruits Images

The growth of the Country's economy highly depends on the agriculture sector. The agriculture agencies are currently working on several agricultural data to increase productivity. Multiple projects are ongoing to boost the agriculture sector. There are many issues such as fungal and bacterial diseases that impede the economic growth of horticulture. Nevertheless, it is a priority for researchers to build a model that can support the prevention, early detection of the diseases and increase production with good quality. The computational approaches play an evolving role in identifying citrus fruit diseases at earlier stages. From the review of literature, the following issues are identified while processing and diagnosis of citrus fruits leaves images using computational approaches.

• In non-uniform lighting conditions, most of citrus leaves images appear darker. Due to the uneven contrasts and visual quality of citrus leaves leads to poor understanding of image features.
• The Citrus leaves images were randomly taken by the farmers using a low-quality camera, hence it may be blurred or unfocused on desired diseased regions.
• The irregular shapes of edges and diverse blending orientations of citrus leaves and fruits images make more difficult to extract features for disease diagnosis.
• Many Citrus leaves boundary are fuzzy in nature, because traditional methods cannot cope with this uncertainty.
• Most of the algorithms failed to separate leaf images from the complex background. Hence, it is difficult to identify the exact boundary of the citrus leaves.
• The edge detection algorithm fails to find which edge pixels should be discarded as noise from the distorted citrus leaves images.
• Due to the variable size, shape and location, variegated color, weak edges, low contrast, irregular and fuzzy borders of the diseased spot of citrus leaves, the image segmentation algorithm fails to extract the diseased region efficiently.
• It is very difficult to identify the exact location of the diseased leaves spot, since the poor quality of images, the presence of extraneous matters and complex image background.
• The majority of unhealthy leaves not identified effectively and the healthy leaves are recognized as diseased leaves due to the deficiencies of the classification models. So the presently available Computational system produces less accuracy.

Performance Measures

The performance matrices are substantial and computable measure used to quantitatively access the performance of Image processing algorithms. To date, researchers have been used specific assessment criteria to measure the efficiency of the proposed methods. The study noted that various metrics used for the diagnosis of diseases in citrus leaves. The short descriptions of these measures are given here along with their formulae.

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) were used to measure the performance of algorithms. The MSE measures the cumulative squared error between the original and the enhanced citrus leaves images whereas the PSNR is the ratio between the squared maximum intensity value of the citrus leaves images and the mean squared error of image.

The Root-Mean-Square Error (RMSE) is frequently used to measure the average of squared differences between enhanced and original citrus leaves images. The SNR is used to measure the random and uniformly distributed noise in the image. It measures how the original citrus leaves images were affected by the noise. It is measured in decibels. SNR metric is used to assess the performance of image compression and preprocessing techniques for citrus leaves images.

Accuracy is the ratio of the number of diseased citrus images that are correctly recognized to the total number of citrus leaves samples. Sensitivity and specificity are the two statistical measures of the performance for binary classification test. Sensitivity measures the percentage of healthycitrus leaves images are correctly identified whereas specificity measures the percentage of diseased citrus leaves were correctly identified.

True Positive Rate (TPR) is the proportion of healthy citrus leaves images that are correctly recognized as healthy samples for all positive data points. The False Positive Rate (FPR) is the proportion of unhealthy samples mistakenly predicted as positive for all negative samples.

Precision measures the overall number of correctly labeled healthy citrus samples divided by a predicted number of healthy samples. It measures the amount of retrieved instances are relevant to the classification. It is also known as Positive Predicted Value (PPV).

Recall is the correct number of positive samples identified divided by the total number of samples. It measures the probability of relevant information that is retrieved successfully among all the relevant instances.

Area Under Curve (AUC) is used in image classification analysis in order to determine which models predict the classes accurately. The performance of the classifier model is calculated by calculating the AUC on Receiver Operating Characteristics (ROC).

Most of the classification problems handle imbalanced datasets. The balance between majority and minority class performance is measured through Geometric Mean or G-mean. The formulas of the above measures are exposed in Table 3.

Discussion

Precise, timely identification and diagnosis of diseases helps for the agriculture growth. Naked eye observation can classify diseases using continuous monitoring experience. But it results in high costs and time consuming. Image processing has been shown to be an important tool for identifying and classifying plant diseases. To address manual process difficulties, many computer-based techniques have been developed in recent years to identify and recognize agricultural and horticultural diseases. The literature review clarified various methods of recognizing and classifying specific citrus plant leaf diseases from 2006 to 2020. From the

Table 3. Performance Measures.

S.No	Performance Measure	Formula
1.	Mean Square Error (MSE)	$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x-1}^{N}\left[I(x,y)-I'(x,y)\right]^2$ I(x,y) - Original image I'(x,y) - Decompressed image M,N - Dimensions of the images
2.	Peak Signal to Noise Ratio (PSNR)	PSNR = 20* $\log_{10}$(255/sqrt(MSE))
3.	Signal-to-noise ratio, or SNR	$SNR = \left[\frac{\sum_i\sum_j (E_{ij})^2}{\sum_i\sum_j (E_{ij}-O_{ij})^2}\right]$ E - Edge detected Image O - Original Image
4.	Root Mean Square Error (RMSE)	RMSE= √MSE
5.	Accuracy	(TP+TN) / (TP+FP+FN+TN)
6.	Sensitivity	TP / (TP + FN)
7.	Specificity	TN / (FP + TN)
8.	AUC	AUC = $\frac{\sum Rank(+)-\lvert+\rvert\times(\lvert+\rvert+1)/2}{\lvert+\rvert+\lvert-\rvert}$ 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
9.	Precision	TP / (TP+FP)
10.	Recall	TP / (TP+FN)
11.	Geometric Mean	GMean =
12.	FPR	FP / (FP + TN)
13.	FNR	FN / (TP + FN)

review, it was proved that the Bagged Tree classifier achieved 99.9% of accuracy to classify grapes leaves diseases. The CNN with transfer learning approach yielded 99.23% of accuracy. The CNN with unitedModel achieved 98.57% of accuracy to recognize grapes leaves diseases. Most of the images used for analysis was taken from the camera, the images may appear noisy. The literature review found that the researchers not focusing on enhancing the quality of the Citrus plant leaves. The researchers will incorporate more innovative algorithms and more methods for improved performance. In future, Online tools and mobile based applications are necessary to provide instant solutions to the farmers regarding the disease severity.

Conclusion

Agriculture plays a vital role in the economic growth of the nation since the majority of developing countries survive on agriculture. Disease normally contaminated agricultural products such as vegetables, fruits. The outbreak of diseases depletes agricultural products quality and quantity. It directly influences the farmer's financial growth and public health. Citrus fruits include lemons, oranges, limes, and grapefruits and enriched with vitamin C, flavonoids that have anti-cancer effects. Plant disease can devastate natural ecosystems, exacerbate environmental problems. Farmers are spending millions of dollars to control citrus plant diseases. The poor disease management without adequate technical support, poor pest control mechanism and naked eye observations of diseases severely affect the production of fruits. Hence, it is essential to identify citrus plant diseases through computational approaches. This paper portrays the survey of computing approaches so for used for analyzing the citrus fruits and leaves images to predict diseases as well as draw decisions for prognosis. This paper also discussed issues related to computational methods in analyzing citrus fruits and its leaves images. There is a need for automatic citrus disease identification, since the existing computational approaches did not provide a complete solution for all the issues related to diagnosing citrus diseases. This study can facilitate the researchers to contribute efficient computational approaches for quick and accurate diagnosis of citrus fruits diseases to increase the cultivation for the farmers.

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